ESSAYS ON MIGRATION

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ESSAYS ON MIGRATION

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ABSTRACT

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Keywords: remittances; child human capital accumulation; adult labor supply; migrant networks; location choice

This dissertation includes two chapters. In the first chapter, we examine the impacts of remittances on various household outcomes including: child school attendance and child illiteracy, child labor, adult labor and household well-being. We use IV estimation technique to account for the endogeneity of remittances. We find evidence of a significant positive impact of remittances on school attendance of 6- to 19-years-old boys and of 6- to 14-years-old girls. Receiving remittances leads to a lower school retention for 15- to 19-years-old girls. Girls of ages 6-to-14 from recipient households are more likely to be literate. Children aged 15 to 19 in recipient households are significantly less likely to supply labor. Adult labor supply results are in favor of income effect hypothesis. Lastly, recipient households are shown to be relatively better-off with respect to welfare compared to non-recipients. In the second chapter, we estimate the determinants of 28-54-years-old male work migrants' location choices among 67 provinces of Turkey. The results show that internal migrants respond to differences in migrant networks, labor market and population attributes between locations while deciding on the migration destination. Distance from the source province is shown to be a significant deterrent of immigrant's location choice. Migrants are drawn to cities in which their former compatriots are highly concentrated. Migrants are more likely to move to cities which have relatively better economic conditions as captured by lower unemployment rate and to cities with larger populations that has larger economic activity.

ÖZET

GÖÇ ÜZERİNE MAKALELER

ERKAN DUMAN

Doktora Tezi, Temmuz 2018

Tez Danışmanı: Prof. Dr. Abdurrahman B. Aydemir

Anahtar Kelimeler: uluslararası para transferleri; çocuk beşeri sermaye birikimi; yetişkin emek arzı; göçmen ağları; yer seçimi

Bu tez iki bölüm içermektedir. İlk bölümde, uluslararası para transferlerinin hanehalklarındaki çocukların okul devamsızlıkları, okur-yazar olma durumları, ve emek arzları; hanehalklarındaki yetişkinlerin emek arzları; hanehalklarının refah düzeyleri üzerine etkisi araştırılmaktadır. Para transferlerinin içselliğini hesaba katmak için araç değişken yöntemi kullanılmaktadır. 6-19 yaş grubu erkekler ve 6-14 yaş grubu kızların okul devam durumları üzerinde para transferlerinin pozitif manidar etkisine delil bulunmuştur. Para transferi almak 15-19 yaş grubu kızların okul devam ihtimallerini azaltmaktadır. Para transferi alan hanelerdeki 6-14 yaş grubu kızların, para transferi almayan hanelerdeki emsallerine kıyasla okur-yazar olma ihtimalleri daha yüksektir. Para transferi alan hanelerdeki 15-19 yaş grubu çocukların emek arz etme ihtimalleri daha düşüktür. Yetişkin emek arzı sonuçları gelir etkisi hipotezinin ağır bastığına delalet etmektedir. Son olarak, para transferi alan hanelerin almayan hanelere kıyasla refah düzeyi bakımından daha iyi durumda olduğu görülmüştür. İkinci bölümde, 28-54 yaş grubu iş amaçlı göç eden erkeklerin Türkiye'deki 67 il arasından yer seçimlerinin belirleyicilerini tahmin etmeye çalışıyoruz. Sonuçlar göstermektedir ki iç göçmenler yer seçimlerini yaparken illerin göçmen ağları, emek piyasaları ve popülasyon özellikleri farklarını göz önünde bulundurmaktadır. Kaynak ilden mesafenin iç göçmenlerin yer seçimleri önünde manidar bir engelleyici olduğu bulunmuştur. İç göçmenler hemşehrilerinin yoğun yaşadığı illere çekilmektedirler. İç göçmenler ekonomik bakımdan daha iyi konumda olan illere ve popülasyonları daha büyük olan illere göç etmeyi tercih etmektedirler.

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1.1 Introduction

With the increase in international migration all over the world, an economic actor paves its way to the stage as an important international financial flow to developing countries-namely, remittances. The beginning of the 1990s witnessed remittances gaining importance over other international financial flows (e.g., foreign direct investment, portfolio investment, and official development assistance) to developing countries. Since the late 1990s, international migrants' remittances have surpassed official development assistance and portfolio investment, and in the beginning of the 2000s, remittances have come very close to the total amount of foreign direct investment flows (Yang, 2011). In 2004, the estimated value of workers' remittances to developing countries was $160 billion, with $40 billion going to Latin America (Acosta, 2006). In 2009 and 2010, remittances to developing countries were $325 billion and $307 billion in nominal terms, respectively (Yang, 2011). The average annual real growth rate of remittances in the period 1999-2008; the decade preceding the 2008 financial crisis, is worthwhile mentioning: while foreign direct investment and official development assistance had average annual real growth rates of 11.0 percent and 5.8 percent respectively in the corresponding period, remittances exceeded both with an average annual real growth rate of 12.9 percent (Yang, 2011).

The excessive amounts of remittances sent to developing countries in the preceding decades and its continued growth has attracted attention of researchers. Motivations behind the decision to remit and development impact of remittances constitute the two broad areas on remittances in the literature. Studies focusing on the former one suggest a number of motives including altruism, exchange for the services provided to the migrant by recipients, insurance, loan repayment, and investment (Brown and Poirine, 1997; Docquier and Rapoport, 2006). Pure self-interest in the form of aspiration to receive inheritance can be added to the list as an important goal in remitting especially when the remittances are sent to the parents' of the migrant and the inheritance is conditional on the behavior of the children (Lucas and Stark, 1985).

Another set of papers study the uses of remittances and simply ask how remittances affect recipient countries or households. Studies trying to find causal linkages between remittances and economic performance at the country level are inconclusive. Faini (2007) finds a positive relationship between remittances and economic growth; however, others find no or a negative relationship (Chami, Fullenkamp, and Jajah, 2003; Giuliano and Ruiz-Arranz, 2005).

Studies using micro level data are partly motivated by the desire to understand remittance impacts in greater detail. In studies on household level impacts of remittances, choices made by the households with respect to the usage of remittances on consumption and/or investment expenditures are frequently observed. There is no widely accepted view on which of these two-alternative use of remittances is desirable. Yang (2011) states that it could be optimal to use remittances on consumption where households suffer from low income levels; whereas, it could be optimal to use remittances on productive investments for households that enjoy a sufficient or a higher wealth level and where productive investments would not have been achieved due to budget constraints without the extra income derived from remittances. Brown and Ahlburg (1999) conclude that increased income derived from remittances is used for higher levels of consumption in South Pacific island states. Yang (2008) shows that there is no correlation between an increase in remittances due to international migrants' favorable exchange rate shocks and consumption expenditures of migrants' origin households in Philippines. However, the exogenous increase in income leads to increased entry into capital intensive enterprises such as transportation and manufacturing by the migrants' origin households in this context.

Investing in the human capital of children is stressed in the literature as an important aspect of investment decisions of remittance receiving households. A sizeable number of studies focuses on the impacts of migration and remittances on educational attainment of children. Cox-Edwards and Ureta (2003) find that remittances reduce the school dropout hazard rates of 6 to 24 years old boys and girls in El Salvador. Acosta (2011), also in the case of El Salvador, finds on average null effect of receiving remittances on the likelihood of children between ages 10 and 18 attending school. When the differences by demographic groups are taken into account, girls between ages 10 and 18 from remittance receiving households are around 10% more likely to attend school compared to non-recipient counterparts, yet the null impact remains the same for boys between ages 10 and 18. Considering the differences by age groups, remittance receiving children between ages 15 and 18 seem to be less likely to attend school compared to non-recipient counterparts, whereas the evidence suggests no difference in school attendance with respect to remittance-receipt status of the household for children of ages

10 to 14. The former and the latter studies use consecutive waves of the nationally representative cross-sectional household survey for El Salvador (Encuesta de Hogares de Propositos Multiples—EHPM) for years 1997 and 1998, respectively. In addition to the differences in estimation samples, above studies also differ in that Cox-Edwards and Ureta (2003) do not address endogeneity of remittances. Yang (2008), in the case of Philippines, states that positive exchange rate shocks for international migrants lead to enhanced human capital accumulation in origin households. His results support the claim that remittances increase child school attendance and educational expenditure. He concludes that a positive exchange rate shock for international migrants is associated with an increase in school attendance rates of 10 to 17 years old girls. However, there is no such causal relationship between positive exchange rate shocks and school attendance rates of 10 to 17 years old boys. Bansak and Chezum (2009) show that, in Nepal, remittances increase school attendance of young children (5 to 10 years old males and females) with the effect being larger for males. They also show that receiving remittances do not change the likelihood of school attendance of old children (11 to 16 years old males and females). Lopez Cordova (2005), in the case of Mexico, provides evidence that remittances decrease illiteracy rates of children aged 6-to-14, and increase school attendance rates of five years old children. However, the impact on school attendance is insignificant for 6- to 14-years-old children and becomes negative for children between 15 and 17. Lopez Cordova (2005) doesn’t investigate whether there is heterogeneity in the impacts of remittances with respect to the gender of the child. Hanson and Woodruff (2003) tried to identify a causal linkage between child schooling and having a household member living abroad for the case of Mexico. Their results imply that 10- to 15-years-old girls whose mothers have less than 3 years of schooling benefit from the migration of a household member with regard to accumulating more years of schooling: additional 0.89 and 0.73 years of schooling for 10- to 12 and 13- to 15-years-old girls, respectively. They also show that migration has a positive impact on the accumulated years of schooling for boys aged 10 to 12, but for this sample, the Sargan-Hansen test rejects the null hypothesis that the excluded instruments are exogenous to the estimation equation. Therefore, the results concerning boys aged 10 to 12 should be approached with caution. Boys and girls aged 13 to 15 from migrant households where mothers have schooling between 3 and 12 years obtain less schooling compared to their non-migrant counterparts. In their study, years of schooling of the mother is used as a proxy for the wealth level of the household. Hence, they argue that migration, via relaxing the household budget constraint thanks to the remittances received, increase years of schooling attained for girls living in households with low income levels. McKenzie and Rapoport (2011) investigate the overall

impact of migration on school attendance and the number of grade years completed for children aged 12 to 18 in rural Mexico. They find evidence of a negative significant effect of migration on school attendance and attainment. Their results show that living in a migrant household lowers the chances of boys completing junior high school and of boys and girls completing high school. Alcaraz, Chiquiar and Salcedo (2012), by exploiting the variation in the remittances—due to 2008-2009 U.S. recession—that Mexican migrants' origin households receive, find that a negative shock to the remittances is associated with a significant decrease in school attendance of 12 to 16 years old children left behind.

Outcomes related to child human capital accumulation is not restricted to child schooling only. Child labor is an outcome as important as child schooling with respect to child human capital investment decisions of households. Labor force participation of a child reduces the time available to spend on education. There is a consensus in the literature regarding the negative correlation between time spent on schooling and on labor for children. Hanson and Woodruff (2003) argues that in poor countries, while deciding on the schooling of the child, the main cost for the household is not the tuition, books, or uniforms but the foregone earnings of the child. Households which would not rely on their children's wage labor are those that can maintain a satisfactory wealth level. In the light of these explanations, increasing educational attainment of children may come through decreasing their participation in labor force and this can be achieved by increasing the income level of households. As a priori guess, remittances by increasing household budget and relaxing liquidity constraints of households may serve this function. There is a large literature on how remittances affect child labor. Yang (2008) makes use of an exogenous variation in origin household's income which results from exchange rate shocks to Filipino migrants and concludes that an increase in the size of the exchange rate shock is associated with a decline in total hours worked by 10 to 17 years old males, while there is no significant association between positive exchange rate shocks and total hours worked by 10 to 17 years old girls. When the composition of the work done is considered, boys aged 10 to 17 work fewer hours in unpaid family work, and work more hours in self-employment; however, the increase in hours worked in self-employment is not enough to cover the overall decrease in total hours worked for boys. An increase in the exchange rate shock is associated with a decrease in hours worked in unpaid family work for girls aged 10 to 17 but the impact is only marginally significant at 10% level. McKenzie and Rapoport (2011), in the case of Mexico, investigate the reason of lower levels of school attendance and years of schooling accumulated for migrant families' children and find as an explanation doing housework for girls between ages 16 and 18 and migrating themselves for boys at all age cohorts (12 to 15, and 16 to 18 years old). There isn't a significant effect of having a migrant household member on 12 to 18 years old boys' likelihood of working as unpaid family workers or as wage earners. Their study reveals that girls between ages 16 and 18 lose on both dimensions—schooling and work experience—of human capital accumulation. In other words, 16 to 18 years old girls from recipient households have lower rates of school attendance and less work experience compared to 16 to 18 years old girls from non-recipient households. Acosta (2011), in El Salvador, finds on average that remittances decrease the likelihood of working for wage and increase the likelihood of working as non-wage laborer (i.e., doing unpaid family work) for children aged between 10 and 18. When the differences in genders are accounted for, girls aged between 10 and 18 from recipient households seem to have lower chances of working for wage or working as non-wage laborer compared to their non-recipient counterparts. Boys aged between 10 and 18 from migrant households are substituting wage labor with non-wage labor. Alcaraz, Chiquiar and Salcedo (2012) find a significant increase in child labor resulting from a decrease in remittance receipts for 12 to 16 years old children in Mexican migrants' origin households.

A substantial part of the literature on the economic impacts of remittances is concerned with the linkage between remittances and labor force participation decisions of adults in origin households. Theoretically, the direction of the impact of remittances on adult labor force participation decisions is uncertain. If migrants' earnings abroad are substantially higher than their corresponding domestic labor market earnings potential, then the remittances sent by the migrants may positively affect the household income. As any other source of non-labor income, remittances will increase the reservation wages of the non-migrants in the household. This income effect may direct non-migrants in the household to substitute labor with leisure: increase the likelihood of leaving the labor force or give them enough motives to stay out of it at all (Killingsworth, 1983). However, if the remittances are channeled to maintain existing household enterprises or to set up a new household enterprise, then there may be an increased demand for labor in the migrants' origin households. This increased demand may reveal itself in two ways: i) by an increase in the labor supply of non-migrants in the household either by new entry to the labor market as non-wage (i.e., self-employed, employer, or unpaid family worker) or wage laborer; or by an increase in the working hours of non-migrants who already participate in the labor force; and ii) by substitution of non-wage labor for wage labor, or by a shift from a category of non-wage work to another category of non-wage work (from unpaid family work to self-employment or vice versa). Increased demand for the non-migrants' labor may deduce from the necessity of replacing the absent migrant's labor and/or income as well as from the productive use of remittances through financing household enterprises which creates its own demand for additional manpower (Binzel and Assaad, 2011). Remittances, by creating opportunities to enter the labor force may give rise to earning own income, and as a result may benefit the non-migrant women in obtaining a higher bargaining power in the household. The empowerment of women in the household may have impacts on the child schooling and child labor decisions, may change the allocation of resources in favor of children; thus, benefit the child human capital accumulation. It is, therefore, necessary to understand the impacts of remittances on the labor force participation decisions of adults and especially of women. Binzel and Assaad (2011), find a significant increase, resulting from the migration of a male household member, in the likelihood of participating in the labor force and in the likelihood of working as non-wage laborer (self-employed, employer or unpaid family worker) for women aged 25-49 in rural Egypt. In the intensive margin, they could not find a significant impact of migration on the working hours of the women left behind. Acosta (2006), in El Salvador, finds a significant negative impact of receiving remittances on the labor force participation of women in the migrants' origin households: women from remittance receiving households are 60 percentage points less likely to participate in labor market. Lokshin and Glinskaya (2009) examines the impact of male migration on prime-age women's labor force participation rates in Nepal and finds that migration of a male household member reduces labor force participation rates of women by 5.3 percentage points. Mendola and Carletto (2009) accounting for remittances effect, find a significant negative impact of current migration experience on the probability of engaging in paid self-employment (of size 54%) and a significant positive impact on the probability of engaging in unpaid work (of size 32%) for Albanian women. There is no impact of migration experience in the household on Albanian men's labor force participation decisions, though. Amuedo-Dorantes and Pozo (2006) by accounting for the endogeneity of remittance income, show that Mexican men reduce work hours in formal sector (i.e., wage and salary work with a contract) and in urban self-employment, and increase work hours in informal sector (i.e., wage and salary work without a contract) due to an increase in the amount of remittances received. Thus, they argue that the disruptive effect of out-migration of a household member outweighs the income effect of remittances on labor supply behavior of males left behind—the forgone income or labor of the migrant, besides related migration costs, seems to be compensated by an increase in the labor supply of other male members of the household in informal sector. Increase in remittances is associated with a decrease both in unpaid family work and in informal work for Mexican women, suggesting dominance of income effect over disruptive effect of remittances. Rodriguez and Tiongson (2001), in Philippines, find that migration reduces labor market participation of 15- to 64-year-old males and females. Nevertheless, their definition of labor market participation includes paid employment and self-employment but excludes unpaid family work, plus the endogeneity of migration is not addressed in their analysis. Cox-Edwards and Rodriguez-Oreggia (2009), in Mexico, find that receiving persistent remittances do not affect labor supply behavior of either men or women of ages 12- to 65-year-old. They argue that the migrant sends back remittances to recover his pre-migration contribution to the household income and the amount of remittances sent is not large enough to alter the prices of labor to achieve a significant difference in non-migrants' labor supply behavior between receiving and non-receiving households.

While a large fraction of the literature on the impacts of remittances is dedicated to human capital accumulation outcomes—child or adult—some focus on the impacts on household well-being. Adams (1998), in the case of rural Pakistan, is unable to find any significant impact of remittances on non-farm asset accumulations. Lopez Cordova (2005) shows that, in Mexico, receiving remittances decreases the chances of households suffering from poverty where poverty is defined as the household income being at most two times of the official minimum wage. However, remittances do not have a significant impact on extreme poverty where extreme poverty cutoff is set at the official minimum wage. Lopez Cordova (2005) argues that high costs associated with international migration is the main reason behind the finding of a zero impact of remittances on extreme poverty. Households suffering from high levels of poverty cannot afford to migrate and send remittances back home. His findings suggest that there is a lower boundary of income for a household to benefit from migration and remittances. Adams and Page (2003), on the other hand, analyze seventy-four countries and show that a 10 percent increase in the amount of remittances received decreases the share of people living under 1 dollar per day by 1.9 and 1.6 percentage points in low and middle-income countries, respectively.

The rest of the paper is organized as follows: the next subsection provides information on migration history of Turkey with a special focus on the important role that remittances play on economic development. Section 1.2 presents the identification strategy, the empirical approach, and a thorough examination of the issues accompanying estimation of impacts of remittances on binary household outcomes. Section 1.3 describes the data and presents descriptive statistics before carrying on with the estimation results in Section 1.4. Finally, Section 1.5 concludes.

1.1.1 Migration and remittance history of Turkey

In the beginning of 1960s, Turkey was experiencing an unemployment rate of 10 percent and an additional underemployment over 15 percent (Icduygu, 2009). Turkish government borrowed heavily from other countries and had difficulties in paying its debts due to the foreign currency bottlenecks (Icduygu, 2009). At the same time, industrialized European countries were in serious need of manpower. In light of these developments, Turkey signed bilateral agreement with Federal Republic of Germany in 1961 that allowed emigration of workers from Turkey to Germany (Koc and Onan, 2004). This was the leading step for the mass emigration of Turkish workers to European countries. The main motivations for the Turkish government in promoting emigration were to reduce unemployment and gain foreign currency through remittances (Icduygu, 2009).

With the opening of the corridor of emigration in 1961, the number of workers going to Europe increased dramatically and peaked at 66,000 people in 1964 (Icduygu, 2009). Till the oil crisis of 1974, mass emigration to Europe continued. 1975 is the last year of observed mass emigration to Europe (Icduygu, 2009). The European countries were deeply affected from the oil crisis and they stopped accepting immigrant workers. Turkish government, then, tried to find new destination routes for its excess supply of labor. The new destination was set to be oil rich Arab countries. Immigrant workers in Arab countries were hired for a specified amount of time—till their assigned project ends—and they were not allowed to bring their families with them (Icduygu, 2005). Over the period of 1975-1980, more than 75,000 contracted workers had gone to the oil-exporting countries (Icduygu, 2009). However, by the mid-1990s, due to the completion of large-scale infrastructural projects most of the immigrant workers had to turn back to Turkey.

With the collapse of USSR in the 1990s, newly emerging countries started reconstruction programs and demanded labor. The mid-1990s experienced mass emigration to CIS countries (former Soviet Republic countries) with a total of 65,000 emigrants (Icduygu, 2009).

In the early 2000s, while Turkey’s population was around 70 million, the emigrants had a total of about 3.5 million. The largest share of emigrants was residing in Europe, a total of 3 million, followed by 300,000 emigrants in Australia, Canada and U.S. The next largest emigrant receiving region is CIS countries with a total of 150,000. Lastly, around 100,000 emigrants were present in Arab countries (Icduygu, 2005). International migrants constituted 5 percent of Turkey’s population.

Between 30 to 40 percent of past emigrants permanently returned back to Turkey (Icduygu, 2005). Besides having 5 percent of the population as current emigrants, this implies that a nonnegligible portion of the population in Turkey has direct migration experience. In addition, emigrants don't lose their contacts with the families left behind and many of them send remittances. A huge migration experience of this sort could potentially have some effects on home country's economy and migrants' origin households.

The most striking impact of emigration on Turkey's economy is through remittances. From 1960s to 2000s, accumulated value of remittances is $75 billion. In 1967, remittances amounted $93 million. In 1974, the corresponding figure was $1.4 billion and, in 1978 remittances amounted $893 million. Between 1978 and 1988 average annual remittances amounted to 1.5-2 billion dollars. In 1980s, remittances amounted 65 percent of trade deficit and 2.5 percent of GNP. During late 1980s and early 1990s, average annual remittance receipt was about $3 billion with a peak of $3.4 billion in 1995 (Icduygu, 2009). In 1990s remittances amounted one third of the trade deficit and less than 2 percent of GNP. In late 2000s, remittances help to cover only around 2% of Turkey's trade deficit. Obviously, it cannot be suggested that the decrease of remittance share of trade deficit and GNP is due to the decrease in annual remittance amounts. The decrease in the share of trade deficit and GNP can be explained with the growth of Turkish economy and lower contribution of remittances in the corresponding shares compared to the contributions from tourism, exporting and other income sources (Icduygu, 2005). It is an undeniable fact that remittances played a major role in financing the import bill of Turkey since 1960s. In addition to providing foreign currency through remittances, emigration also relieved the pressure on unemployment rates. Turkey had experienced an unemployment rate of 16.7% in 1986 and it is argued that the unemployment rate would have reached 23.2% in 1986 in the absence of labor emigration (Barisik et al., 1990). As a result, it can be argued that a successful policy was run in Turkey to overcome the foreign currency bottlenecks and to reduce unemployment.

Even though Turkey has an impressive migration history and has accumulated significant amounts of remittances, there are very few studies regarding the impacts of international migration and remittances in the context of Turkey.

There is a well-known migration study in Turkey; 1996 Turkish International Migration Survey (TIMS-96). Data was collected from 28 selected districts in 8 provinces of Turkey in 1996 and was not representative at the national level. According to TIMS-96, 12 percent of households received remittances and 80 percent of remittance receiving households used remittances to improve their standard of living. In TIMS-96, there is also evidence for regional differences in the amount of remittances received. It is found that households located in less developed regions are more likely to receive remittances than households in developed regions. Koc and Onan (2004), by using data from TIMS-96, find that remittances are basically used to satisfy consumption needs of origin households. This is a conflicting result with findings of Yang (2008) who shows that increased remittance income deriving from international migrants' exchange rate shocks is not associated with any change in consumption of origin households in Philippines. Koc and Onan (2004) also show that remittance receiving households are better off than non-recipient households. This implies that remittances have a positive impact on household welfare. Day and Icduygu (1999) use data gathered from 234 individuals in Turkey during 1992-1993 and show that return migrants and their close relatives have higher consumption levels than non-migrants. Keles (1985) conclude that remittances do not work in the direction of reducing imbalances between regions of Turkey, but benefit the remittance receiving households via improving their standards of living. Atalik and Beeley (1993) find that remittances are used for investment in physical capital such as acquisition of land, and cars.

In the Turkish context, there are some studies on the determinants of remittances[1], to the best of our knowledge, impacts of remittances on different aspects of human capital accumulation were not studied thoroughly. In addition, datasets that were used in prior studies on impacts of migration and remittances in the context of Turkey were not nationally representative which poses problems for the external validity of the estimates. This study, by implementing a nationally representative micro level dataset, aims to fill this gap and contribute to the literature by studying the impacts of remittances on child schooling, child illiteracy, child labor, adult labor force participation and household wellbeing in the context of Turkey. Furthermore, much attention has been paid to solve econometric problems associated with estimation of binary choice models with a binary endogenous variable.

1.2 Identification Strategy and Estimation Methodologies

1.2.1 Econometric Identification

Hoddinott (1994) states that migration decision is an outcome of a utility maximization problem of the household solved jointly by the prospective migrant and the other household members. Thus, the allocation of migrants and migrant earnings across households may not be random. The main empirical challenge in consistently estimating the causal impacts of remittances on schooling/labor outcomes is due to a possible correlation of households'

[1] Aydas et al. (2005), Köksal (2006), Van Dalen et al. (2005)

remitting behavior with unobserved determinants of outcomes. For instance, the education mobility literature presents evidence of a positive association between parents' heritable schooling endowments and their children's educational attainment[2]. In addition to this linkage between parents' ability and their children's schooling outcomes, if parents with higher heritable genetic ability find it more appealing to migrate and remit in order to finance their children's schooling expenses, then a simple comparison of remittance receiving and non-receiving families overestimates the impacts of remittances on child schooling. Hanson and Woodruff (2003) presents a different scenario: households which experience negative income shocks may decide to send a member abroad to cover the financial losses. Children in such households may need to reallocate their time favoring labor over schooling to compensate for the short-term income shortages resulting mainly from the unfavorable shock. A comparison of remittance receiving and non-receiving families, in that case, will understate the education gains from remitting. Therefore, the direction of endogeneity bias is uncertain. Moreover, reverse causality problem may arise if families consider migration and remittances as a leeway for funding their children's education.

To solve the endogeneity problem of remittances, we implement an instrumental variable estimation strategy and follow McKenzie and Rapoport (2011) and a number of studies[3] in using regional level historical migration rates as instruments. International migration incurs some substantial costs: monetary costs related with transportation, costs of acquiring information about the destination country, opportunity costs in terms of lost income while searching for jobs in the destination country, and psychic costs related with losing contact with parents, beloved ones, friends and relatives (Massey, 1988). Migration networks help lowering these costs by providing a prospective migrant information and help about ways to enter the destination country, finding job, accommodation and adapting to a new culture. Households with better access to migrant networks bear a lower cost of migration, and thus, are more likely to migrate and send remittances. Migration stocks become self-perpetuating via cost lowering impact of migrant networks, and thus, migration networks formed earlier affect migration decisions of households today (Munshi, 2003; McKenzie and Rapoport, 2007). Migration rates are argued to be good indicators of migration networks present in a village, municipality or a

[2] Holmlund, Lindahl and Plug (2011), Behrman and Rosenzweig (2002)

[3] Hanson and Woodruff (2003), McKenzie and Rapoport (2011), Hildebrandt and McKenzie (2005) all use historical migration rates as instruments to predict current migration stocks. Acosta (2011) uses historical migration rates as instruments for receiving remittances on the household side. Alcaraz et al. (2012) and Lopez Cordova (2005) use the placement of rail lines in Mexico in 1920 -the distance from municipality to the rail road plus the distance from the rail road to the US-Mexico border-, which mainly captures migration networks present in municipalities, to instrument current remittance receipts.

state (Hanson and Woodruff, 2003). Consequently, historical migration rates may serve as instrumental variable for current migration decision of households and remittance receipts. The migration rate we use comes from the 1985 Turkey Census data and is calculated as the share of international migrants in a region's population. The international migrants are defined as those Turkish citizens who had changed their residence country to Turkey from a host country during the previous five years. There are 26 regions in Turkey which are statistical agglomerates of provinces and each region consists of provinces which are similar in characteristics such as population, socioeconomic development, geography, per capita GDP, per capita output in industry, agricultural output, and urbanization rate[4]. We calculate historical regional migration rates by taking a weighted average of 1985 migration rates of provinces in a given region where a province's weight is equivalent to the population share of that province in the region.

IV estimation relies on mainly two assumptions; migration networks should be strongly correlated with remittances, and migration networks should not affect potential outcomes other than their impact through remittances. These assumptions are known as existence of first stage and exclusion restriction of the instrument, respectively. Existence of first stage is argued to hold via cost lowering impacts of migration networks which induce continuing waves of migratory movements from a region and continuing remittance receipts in a region because of the sustained migration. Furthermore, existence of first stage could be confirmed through running a regression of remittance receipts on migration networks. Many studies successfully establish a strong correlation between migration networks and remittance receipts[5]. The challenging part is to justify the exclusion restriction of the instrument.

There are some potential threats to the exclusion restriction; hence, to the validity of the instrument. Woodruff and Zenteno (2001) is one of the pioneers in forming the sociological linkage between migration networks and current migration flows. Studies thereafter make use of the instrument in predicting current migration and remittances. However, for migration networks to instrument remittances, one needs to assume that the only impact of migration networks on outcomes is through remittances. If there are other impacts of migration on outcomes that are distinct from remittances, then the error term will capture these impacts and migration network will eventually be correlated with the error term since migration networks are good predictors of migration (McKenzie, 2005). The literature presents evidence on migration having impacts different than and most likely conflicting with its most apparent

[4] The regional classification used in the study is provided by TÜİK and is at NUTS-2 level.

[5] Acosta (2011), Alcaraz et al. (2012), Lopez Cordova (2005), Bansak and Chezum (2009), Cattaneo (2012)

impact; remittances. Hanson and Woodruff (2003) note that migration may disrupt the family structure and leave children in migrant households without a guardian or a role model. In addition, children may be forced to participate in labor market to compensate for the lost income of the migrant family member. McKenzie and Rapoport (2011) state that children of migrant families are more likely to migrate than children of non-migrant families. If there are differences in returns to education in source and host countries, this may incentivize children of migrant families to substitute education with migration or vice versa. Trying to isolate the impact of remittances from other impacts of migration by means of instrumenting remittances with migration networks may lead the instrument to capture these other impacts of migration which is a violation of exclusion restriction (McKenzie, 2005). Thus, to estimate pure impact of remittances (income effect), one may need to account for other impacts of migration while instrumenting remittances with migration networks[6], or try to find an instrument which predicts not only why one household is more likely to have a migrant member compared to an observationally similar household, but also why one migrant family sends more remittances compared to an observationally similar migrant family[7]. Hence, most of the studies that instrument remittances with migration networks are likely to estimate the combined impact of remittances and other impacts of migration[8]. In other words, they implicitly estimate the overall impact of migration. In this study, we acknowledge that the main interest is not to estimate pure monetary impacts of remittances, instead it is argued that the remittance receipt status is a good proxy for the migration experience of a household. In our data, among remittance receiving households 36.5% of them have either a missing male or a missing female spouse of the household head. Although, information about the migration experience of household members or information about the household members who are absent at the survey date are not available, we are inclined to think that the missing male or female spouse is the source of the remittances. This assumption, if true, may imply either a recent or a past migration experience for a household. Regarding this last point, 11% of remittance recipient households with a missing male spouse, receive remittances in the form of pension benefits only, and almost 90% of

[6] Bansak and Chezum (2009), in the case of Nepal, account for the household disruption impact of migration by controlling for the number of adults living outside the household.

[7] Yang (2008), in the case of Philippines, induces exogenous variation in amount of remittances through exchange rate shocks which are argued to be randomly distributed over migrant households. Yang (2008) considers only the households with international migrants before the unexpected Asian financial crysis in 1997 and uses the change in the exhange rate as the treatment which is argued to be randomly distributed across migrants and shows that the elasticity of remittances with respect to exchange rate is 0.6.

[8] Bansak and Chezum (2009), Yang (2008) and Lopez Cordova (2005) differ from the rest of the studies as their identification strategies try to isolate the impacts of remittances from other consequences of migration.

female household heads in these households have either lost or divorced their spouses. The corresponding share of households with missing female spouses which receive remittances in form of pension benefits only is 37%, and 74% of the male household heads either have lost or divorced their spouses. These statistics lead us to imagine that either the spouses that we observe in the data or their counterparts had a past migration experience. For households with a missing male spouse which receive remittances in forms other than retirement pensions, 67% of the left behind female partners are married and 23% of them have a passed away spouse. This may suggest that the husbands or the husbands' close relatives may provide the female household heads with remittances, even though there is no evidence to prove the latter. This observation, contrary to the preceding case, suggests a recent migration impact on the household and provides us with more confidence in assuming that the source of the remittance is the spouse living outside the house. Another channel to link remittances with the migration experience of household is through the observation that recipient households of pension benefits from a host country where both partners are at home constitute 27% of all remittance receiving households. This is an indicator for return migration within the household. In total, almost 64% of remittance receiving households can be linked to the source of the remittance, and hence, can be attributed with a possible migration experience. The rest of the recipient households may receive the remittances from other household members (e.g. children, or grandchildren), close relatives to the family, or friends albeit there is no way to confirm the source of the remittances in this case. Acosta (2011) uses cross sectional data from El Salvador and finds that nearly 30% of recipient households receive remittances from outside their circle of close relatives. Our data is in line with Acosta (2011) regarding the relationship of the remitter with the family left behind. Still, the descriptive evidence suggests a strong relation between remittances and households' migration experience.

Migration is defined in a variety of ways in the literature. Some use narrow definitions of migration[9] which is good at unraveling the impacts of migration that may have occurred concurrently with the incidence of migration. Some use broader definitions of migration[10]. Migration may have long-lasting impacts, that is, the impacts may have been preserved for a long period of time. The change in household resources due to the migration of a household member six or more years ago may still affect the households' schooling decisions for their children. The negative impacts of a household member's migration six or more years ago, for

[9] Hanson and Woodruff (2003), Lopez Cordova (2005) define migration as the change of residency within last 5 years from source country to a host country.

[10] McKenzie and Rapoport (2011) define migration as ever been to another country for work or other reasons.

example, might have forced children to leave the school when they were young and it is likely that these children will not be observed at school when they get older.

This scenario bears an impact of migration at the extensive margin, and migration defined as change of residency within the last 5 years or having a current migrant member may be insufficient to reveal the impacts of migration at the extensive margin. Especially, when the interest is to find the impacts of migration on schooling and child labor, making use of the broad definition of ever migrating allows to estimate such persistent impacts. The remittance variable in our study, by the inclusion of households that receive remittances as retirement pensions besides in cash and in-kind, capture both past, recent and current migration experience of households, in other words, whether households have ever engaged in migration. To sum up, remittance receipt of households is argued to capture not only income effect of remittances but also other consequences of migration experience, and is used to estimate average impact of ever migrating on households. To be precise, IV methods estimate local average treatment effects; the effects on the group of compliers. These are the units that take the treatment when they are exposed to the instrument, and do not take the treatment when they are not exposed to the instrument. In our study, households that receive remittances when they have a large migrant network and do not receive remittances when they have a small migrant network comprise the complier group. McKenzie and Rapoport (2007) show that these households come from the lower end of the wealth distribution as they cannot afford migration unless they have access to a large migration network that help reduce the migration costs hugely. This is a group worth investigating the impacts of migration because remittances may benefit them more compared to households that come from upper parts of the wealth distribution.

Another threat for the validity of the instrument is that migration networks measured by regional migration rates in 1985 can predict outcomes through means other than remittances. This is possible, in particular, if there were regional characteristics that influence migration historically and persist to influence outcomes of interest today. Being unable to account for all possible channels distinct from remittances, through which migration networks may explain part of the variation in outcomes, results in violation of the exclusion restriction and renders the instrument invalid. The initial emigration to Europe from Turkey between 1961 and 1974, which helped creating migration routes that prospective migrants follow, was heavily organized by Turkish Employment Service (TES). Unless a specific worker is demanded by the employer in the host country, an individual had to apply to a local TES office located mostly at city centers and register his name in a waiting list. Whenever a job position opens, it was offered to the relevant candidate in the waiting list by TES (İçduygu, 1991). Back then, the Turkish government desired mass flows of emigration to Europe in order to reduce unemployment, gain foreign exchange earnings through remittances, and provide grounds for development projects for the underdeveloped regions of the country. With regard to the last point, emigrants from relatively poor regions of the country and from regions of natural disasters were prioritized by TES to migrate at once (Abadan-Unat, 2006). Day and İçduygu (1997) comment on the relationship between socioeconomic development of regions and emigration in Turkey, and show that when the regions get poorer emigration increases, but when socioeconomic development falls below a certain level, emigration levels start to decline as well. It can be considered within this context that in 1960s and 1970s, some poorest cities in less developed Eastern Anatolia region never achieved to become significant emigration sources whereas, relatively poor cities like Denizli, Afyon and Yozgat from more developed Western and Central Anatolia regions were the main sources of emigration to Europe (Ayhan et al. 2000). Apparently, the creation of migrant networks was influenced partly by regional disparities in development levels, and it is implausible to assume that migration networks are distributed randomly across regions. If historical inequality in development levels, besides helping determine the migration networks, also continue to influence schooling and labor today then it is necessary to account for historical levels of inequality to preserve the validity of the instrument. Historical schooling differences between regions may also pose problems for the exogeneity of the instrument. If historical schooling levels vary accordingly with migrant networks and have impacts on current schooling levels (i.e., through intergenerational transmission of schooling), then not addressing this channel would invalidate the instrument. It is likely to observe a relation between historical schooling levels and historical migration networks as schooling levels are good predictors for level of development in a region, and it is shown that historically high emigration regions are less developed (Ayhan et al. 2000). To account for historical schooling and historical inequality levels, we control for regional measures from around the same time period as our instrument: length of road per 1 km^2 by region in 1980, the share of length of asphalt roads in total length of roads by region in 1985[11], the interaction between these two variables, development index values from 1973[12], school

[11] The information necessary to create road related variables is acquired from General Directorate of Highways Maintenance Division.

[12] DİE (Devlet İstatistik Enstitüsü) 1973: 72-5. DİE estimates the development index for each province considering the following indicators: proportion of urban population, literacy rate, number of high school and university graduates, paid income tax per capita, number of hospital beds per 100,000 persons, number of persons per radio, length of road per 1 km^2, average number of workers per workplace, per capita added value, per capita industrial added value, proportion of agricultural workers in total workforce, and share of industrial laborers in total workforce. We take a weighted average of provinces' index values with respect to their population shares in the region (1970 Census is used to gather the information on provinces' populations). The higher the index value the higher the development level is. The index value for the country is standardized at 1.

attendance rates for males and females aged between 6 and 10 by region in 1985, number of schools per 1,000 children aged between 6 and 16 by region in 1985[13].

Turkish government aimed to increase the standard of living for citizens residing in relatively poor regions or natural disaster areas by giving them priority in migration and facilitating their move; however, the only interest of the government was not the welfare of the emigrant households. Turkish government also considered migration and remittances as a means of speeding up the development process of underdeveloped regions, and in order to achieve this goal tried to channel migrants' earnings to employment generating activities in less developed regions via the installation of three development programs in 1970s (Keleş, 1985; Martin, 1991). Firstly, *Worker's Joint Stock Companies* were founded to foster the development in less developed regions and hence, reduce regional disparities. Migrants' remittances and non-migrant households' contribution in migrant sending regions were the main two sources of financing these institutions. The investments made by these institutions would benefit returning migrants in finding jobs and serve as a tool to develop regions of origin. Secondly, Turkish government initiated the establishment of *Village Development Cooperatives* in mostly poor regions of the country, and remittances served as one of the main funding through which Village Development Cooperatives operate. These Cooperatives had a nonnegligible impact on the development of various migrant sending regions; as an example, Boğazlıyan, which is a town of Yozgat and is one of the main migrant sending regions to Europe, experienced a rapid increase in the number of agricultural machineries from 300 in 1966 to 1,500 in 1975 thanks to investments made possible by migrants' earnings (Abadan-Unat et al. 1976). Besides improving backward regions, these Cooperatives also offered migration possibilities to its members, since members of Village Development Cooperatives in poor regions had priority in migrating, and the huge increase in the number of Cooperatives from 2,000 in 1971 to almost 6,000 in 1974 reveals the role of Cooperatives in easing migration (Abadan-Unat, 2006). It can be argued that there is a two-way relation between migration from and development of migrant sending regions: more migration might have accelerated development of the source regions for migrants through investments of government initiated development programs which as discussed mainly operate on migrant earnings, and these institutions besides contributing to the development process of emigrants' source regions might have increased the stock of migrants from these regions via facilitating migration. Lastly, *State Industry and Workers' Investment Bank* was

[13] We benefit from National Education Statistics 1985-1986 which is published by DİE with regard to number of students enrolled and number of schools for related age categories, and for the total number of children in given age categories we make use of 1985 Turkey Census.

founded in 1975 to direct migrants' earnings into establishment and development of various industries all around Turkey (İçduygu, 2009).

The first two development programs were effective in developing migrant sending regions in need of extra funding to catch up with the development level of other parts of the country; however, the last program proved to be ineffective in developing the poor regions. These development programs suggest that flows of remittances might have generated new employment opportunitites and allowed infrastructural investments in migrant sending regions such as school facilities and health facilities which in turn, might have changed the income distribution and the incentives and capabilities for the households to invest in their children's schooling today. Ayhan et al. (2000) argues that many migrant sending regions have better, more grounded, or more effective economies as a result of migration. To allow for the possibility of migration and remittances having differential impacts on development levels of regions, we control for gini of household income by region and school attendance rates for males and females aged 15 to 19 years old by region both measured as averages over the years 2003 and 2011 (the years considered in this study). Furthermore, in labor market participation regressions we include other relevant controls that capture labor market characteristics of regions: share of men between 25 and 64 years old with high school degree by region, share of men between 25 and 64 years old with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region, all calculated from the data as averages over the years 2003 and 2011. We apply Spearman rank correlation tests between our instrument and the regional controls to see whether our concern about the exogeneity of the instrument is valid. The results show some significant correlations: regions with high historical migration rates were more developed in 1973, have higher shares of asphalt roads in 1985, have higher school attendance for 6 to 10 years old boys and girls in 1985, have higher average school attendance for 15 to 19 years old girls, have higher share of men aged 25-64 with above high school degree, and have lower share of men aged 15-64 working in agricultural sector. In addition to the regional characteristics we control for, we provide around 20 years lag in our instrument to exempt from the concerns of the instrument predicting current economic conditions of regions and reverse causality. The first stage regression results are presented in Tables between 1-5 and 1-8, and show that the instrument has strong predictive power for households' remittance receipt status even after controlling for numerous regional characteristics.

Migration networks may also directly affect outcomes of interest. The presence of migrant households in the neighborhood may change children's attitudes towards schooling and labor. Although the presence of a migrant member in the household has more pronounced impacts on the children compared to the presence of migrants in the neighborhood, such an impact would threaten the validity of the instrument. Since the instrument is assumed to be exogenous conditional on covariates, to test the exogeneity assumption of our instrument, we use only the sample of non-receiving households and regress outcomes of interest (school attendance and labor participation of children, participation decisions of adults, and household well-being) on a dummy taking value 1 if the observation belongs to a high migration region in the past—regions that are above the median migration rate in 1985—in addition to regional controls and other individual and household level covariates that are relevant. The results are presented in Appendix Table A1, and provide further evidence on the exogeneity of the instrument[14], and thus, the validity of the instrument.

There is one last assumption to satisfy in an instrumental variable estimation; monotonicity. This assumption requires the population to be divided into three subgroups consisting of compliers, always-takers and never-takers. That is, population shouldn't include defiers (Imbens and Angrist, 1994). In our context, monotonicity assumption means that households that receive remittances when they have a small network should do so when they have a large network. Although testing monotonicity is not possible with the data in hand, it is a tenable assumption as migration incurs some substantial costs and households that can cover these costs and send remittances without relying heavily on migration networks could do so when they are to reside in regions with larger migrant networks. Under monotonicity assumption, the linear IV estimator (IV 2SLS) recovers local average treatment effect of remittances which is interpreted as the average treatment effect of remittances on the group of compliers by Imbens and Angrist (1994).

[14] This indirect test of exogeneity is actually an empirical application of the exclusion restriction of the instrument explained by Abadie (2003: 234). The mathematical formulation is $P(Y_{0d} = Y_{1d}|X) = 1 \; for \; d \in \{0,1\}$ where d represents the treatment status, P is a probability function, X is a set of exogenous covariates, and Y_{0d}, Y_{1d} are potential outcomes when not exposed to and exposed to the instrument, respectively. Within our context, whenever $d = 0$ which corresponds to the case of non-receiving households, this equality implies that having a large migration network—being in a region that is above the median migration rate in 1985—shouldn't have any influence on outcomes of interest conditional on covariates. McKenzie and Rapoport (2011) employs the same strategy to check the exogeneity of their state level instrument. Abadie's formulation suggests that having a large migration network shouldn't affect outcomes for treated samples, too. Our experiments with remittance receiving samples yield insignificant impacts of being in a high migration region on outcomes which implies that having a household member engaged in migration activities is more influential compared to having a migrant in the neighborhood.

1.2.2 Other Estimation Issues

This study tries to estimate binary choice models (i.e., school attendance, labor force participation) with binary endogenous regressor (i.e., receive remittances). The literature presents evidence on estimation of this sort of models mostly by means of linear instrumental variables (IV 2SLS) and maximum likelihood bivariate probit estimation methods (IV bivariate probit)[15]. There is no consensus on the preferred specification of the model: Angrist (1991, 2001) stresses directly interpretable causal effects and robustness of linear instrumental variables to non-normality of error terms; while Altonji et al. (2005) argue that maximum likelihood bivariate probit provides more reliable coefficient estimates compared to linear IV estimation, and Bhattacharya et al. (2006) advocate that IV bivariate probit is slightly more robust to non-normality of error terms. Chiburis et al. (2011) extend the set of parameter values that were used in simulations by Angrist (1991) and Bhattacharya et al. (2006) and try to provide more insights into the best practice of action for estimating bivariate binary-choice models with an endogenous treatment. The findings of Chiburis et al. (2011) can be summarized as follows: (i) when treatment probabilities are low, for all values of outcome probabilities[16] and even in samples with more than 10,000 observations, the confidence intervals of linear IV are much larger compared to confidence intervals of bivariate probit which may render hypothesis testing uninformative for linear IV estimation and in addition may explain some portion of the observed large differences between linear IV and maximum likelihood bivariate probit estimates in the literature; (ii) in general, confidence intervals of linear IV are too large and confidence intervals of IV bivariate probit are too narrow; (iii) when treatment probabilities are low and bivariate probit model is misspecified (i.e. when error distributions have excess skewness or excess kurtosis), bivariate probit estimates are severely biased and Wald tests based on bivariate probit estimates tend to reject a true null hypothesis too often; however, misspecification does not cause biased estimation of parameters in bivariate probit models with no covariates. The presence of covariates in the model accentuates the problem of large standard errors for linear IV. An important conclusion of Chiburis et al. (2011) is that bivariate probit is generally more efficient compared to linear IV especially when there are covariates in the model. Their study concludes with three main suggestions for researchers: (i) present both linear IV and bivariate probit estimates when there are covariates in the model and treatment probabilities are low; (ii)

[15] Acosta (2006) implements linear IV estimation; Görlich, Toman, and Trebesch (2007) implements bivariate probit estimation; McKenzie and Rapoport (2011), and Acosta (2011) implement both types of estimation methods.

[16] The range for outcome probabilities is 0.1-0.9, and 0.1 chance of receiving treatment is defined as low treatment probability.

use bootstrapped standard errors and percentile based confidence intervals to improve over and undercoverage of linear IV and bivariate probit confidence intervals, unless the sample size is at least 10,000; (iii) and use Murphy's score test (Murphy, 2007; Chiburis, 2010) to check the goodness-of-fit of bivariate probit model. In our data, the share of remittance receiving households is around 0.015; thus, the estimations are most likely to suffer from low probability of receiving treatment. Furthermore, Murphy's score test presents evidence on departure from bivariate Gaussian distributed errors assumption in most of the estimations when IV bivariate probit is the preferred estimation method; hence, raises questions about the reliability of coefficient estimates from IV bivariate probit and statistical inference from linear IV estimation. Lastly, in some specifications[17] linear IV estimates of local average treatment effect (LATE) are outside the unit interval; albeit, both average treatment effect (ATE) recovered from IV bivariate probit estimates and IV estimates of LATE must lie in interval [-1,1] (Chiburis et al., 2011). This is an indication of linear IV estimation performing poorly when the treatment probabilities are low and outcome probabilities are high; an established result due to Altonji et al. (2005)[18] and Chiburis et al. (2011). IV bivariate probit estimates of ATE, in contrast, stays in unit interval as IV bivariate probit fits a non-linear function through the data.

Problems associated with parametric estimation methods for binary choice models with a dummy endogenous regressor direct our attention to semiparametric and nonparametric estimation methods. The literature presents various approaches for semiparametric estimation of binary choice models (see, Manski, 1975; Gallant and Nychka, 1987; Powell, Stock, and Stoker, 1989; Ichimura, 1993; Klein and Spady, 1993). This study benefits from the semi-nonparametric approach of Gallant and Nychka (1987)—will be referred as SNP from now on—which was adapted by De Luca and Peracchi (2007) to estimate bivariate binary choice models[19]. SNP estimation applies Hermite polynomial expansions to approximate the unknown joint density of error terms[20], and uses these approximations to derive pseudo log-likelihood function, and eventually, estimates the model parameters by maximizing the resulting pseudo log-likelihood function. A large class of densities can be approximated by this functional form

[17] School attendance regressions for boys and girls aged 6-14 or 15-19.

[18] Altonji et al. (2005) show that linear IV estimation when applied to bivariate-binary choice problems perform well only in cases where binary groups have almost equal probability, within our context, proportion of students attending school is high, and the proportion of households receiving remittances is low.

[19] De Luca (2008) presents Stata routine for SNP estimation of univariate and bivariate binary choice models.

[20] For bivariate binary choice models, the unknown joint density of latent regression errors $f(u_1, u_2)$ is aprroximated by Hermite polynomial expansion of the form: $f^*(u_1, u_2) = \frac{1}{\psi_R}\, \tau_R(u_1, u_2)^2\, \phi(u_1)\, \phi(u_2)$ where $\phi(.)$ is standard normal density function, and $\tau_R(u_1, u_2) = \sum_{h=0}^{R_1} \sum_{k=0}^{R_2} \tau_{hk} u_1^h u_2^k$ is a polynomial in u_1 and u_2 of order $R = (R_1, R_2)$, and ψ_R ensures that $f^*(u_1, u_2)$ is a proper density function.

which includes densities with arbitrary skewness and kurtosis (Gallant and Nychka, 1987). The main difference between bivariate probit and SNP estimation is the ability of SNP estimation to deal with a broader set of error distributions. Gallant and Nychka (1987) has shown that under weak distributional assumptions on error terms[21], the pseudo maximum likelihood estimators for model parameters are $\sqrt{n}$ consistent provided that the orders of the Hermite polynomial increase with sample size. SNP estimation can recover consistent parameter estimates whenever the bivariate standard normal distributed latent regression errors assumption of bivariate probit model cannot be satisfied; in other words, whenever the bivariate probit model is misspecified. Thus, SNP estimation can be considered as a direct extension of bivariate probit estimation. Although Gallant and Nychka (1987) do not provide distributional theory for SNP estimator, De Luca (2008) argues that for fixed orders R_1 and R_2 of the Hermite polynomial expansion statistical inference can be conducted as if the model was estimated parametrically. The underlying assumption is that the true joint density function of errors belongs to the class of densities that can be approximated by a Hermite polynomial expansion with orders R_1 and R_2. Hence, the selection of orders of the Hermite polynomial expansion becomes an important ingredient in the model specification. For error terms to have skewness and kurtosis different than that of a standard normal distribution, the values of the orders should satisfy $R_1 \geq 2$ or $R_2 \geq 2$. Likelihood ratio tests or model-selection criteria such as Akaike information criterion or Bayesian information criterion can be used to choose among possible values of R_1 and R_2. In this study, we test with values of orders $R_1 = R_2$= 3, or 4, and choose the model with the lowest value for model selection criteria and with lowest p-value of the Wald test for the instrument in the equation for the determination of remittance receipt (first stage equation). Monte Carlo simulations run by De Luca (2008) show that with large sample sizes (n=2,000) the efficiency losses of SNP estimator compared to bivariate probit estimator when there is no departure from bivariate Gaussianity assumption, are very small; in addition, the mean squared errors of the SNP estimates are very close to mean squared errors of bivariate probit estimates. However, when the errors have joint distributions other than bivariate Gaussian distribution and sample sizes are large, SNP estimator dominates bivariate probit estimator both in terms of efficiency and mean squared errors of the estimates. Although, De Luca (2008) shows that rejection rates of Wald tests for SNP estimates being equal to the true parameter value are lower than those of bivariate probit estimates when the bivariate probit

[21] Error densities that exhibit violent oscillations, and error densities with too fat or too thin tails are shown to be outside the class of densities that can be approximated by Hermite polynomial expansions (Gallant and Nychka, 1987).

model is misspecified and the sample size is large, they are far from the nominal value of 5%. De Luca (2008), due to time constraints, only try orders $R_1 = R_2 = 4$ for polynomial expansion and argues that this particular value of orders may not equip Hermite polynomial expansion the capability to approximate the true joint density of errors. This finding stresses the importance of making effort to choose correct values of polynomial orders in order to achieve reliable statistical inference. Moreover, De Luca (2008) argues that poor coverage rates of SNP estimator could be improved via implementing Huber-White sandwich estimator for standard error estimation.

We estimate several binary choice models for school attendance of children aged 6-14 and 15-19, illiteracy for 6-14 years old children, labor force participation of children aged 15-19 and of adults aged 20-64, and household well-being, and present four different estimates, namely parametric non-IV estimates from probit models, parametric IV estimates from linear IV and IV bivariate probit models, and semiparametric IV estimates from SNP models.

The binary choice models we estimate are of the following form:

$$\begin{gathered} Y_{ijtg} = \alpha + \delta_t + \beta T_{jtg} + X'_{ijtg}\gamma + Z'_{jtg}\eta + W'_g\theta + u_{ig} \\ i = 1, \ldots, N_g, \qquad g = 1, \ldots, 26 \end{gathered} \tag{1}$$

$$\begin{gathered} T^*_{jtg} = \vartheta + \pi_t + \zeta M_g + X'_{ijtg}\gamma_T + Z'_{jtg}\eta_T + W'_g\theta_T + u_{Tig} \\ T_{jtg} = 1\{T^*_{jtg} > 0\} \\ Y^*_{ijtg} = \varphi + \omega_t + \xi T_{jtg} + X'_{ijtg}\gamma_Y + Z'_{jtg}\eta_Y + W'_g\theta_Y + u_{Yig} \\ Y_{ijtg} = 1\{Y^*_{ijtg} > 0\} \\ i = 1, \ldots, N_g, \qquad g = 1, \ldots, 26 \end{gathered} \tag{2}$$

For the models described i denotes individuals, j denotes households, g denotes regions, and t denotes years. There are 26 regions, and each region g has N_g observations. The coefficients with a subscript t estimate year fixed effects. Y_{ijtg} represents an outcome of interest (school attendance, labor force participation decision, etc.) from year t for an individual i residing in household j in region g. T_{jtg} takes value 1 if household j in region g from year t receives remittances, and 0 otherwise. M_g corresponds to continuously distributed migration network variable, and is used to instrument the household's remittance receipt status. X_{ijtg} is a vector of individual characteristics, Z_{jtg} is a vector of household characteristics, and W_g is a vector of regional controls that doesn't vary across years, $u_{(.)}$ represents corresponding error terms.

We use probit and IV 2SLS to estimate (1). IV 2SLS does not take into account the binary nature of the dependent variable, but addresses self-selection into treatment via instrumenting the remittance receipt status of households with migration networks. Probit estimation, on the other hand, takes into account the binary nature of the dependent variable, but cannot handle endogeneity of the remittance receipt. Probit estimates are presented to see whether self-selection of households into receiving treatment is a major issue.

If the interest lies in modeling the joint probability of binary indicators Y_{ijtg} and T_{jtg}, a latent linear index model as in (2) can be implemented. T_{jtg}^{*} and Y_{ijtg}^{*} are unobserved latent variables, and the association between observable binary indicators and latent variables is through the rules $T_{jtg} = 1\{T_{jtg}^{*} > 0\}$ and $Y_{ijtg} = 1\{Y_{ijtg}^{*} > 0\}$ where $1\{.\}$ is an indicator function taking value 1 if the statement inside the brackets is correct, and 0 otherwise. When latent regression errors u_{Tig} and u_{Yig} have bivariate standard normal distribution with zero means, unit variances and correlation coefficient ρ, model (2) is known as bivariate probit (Heckman, 1978). If, in addition, (u_{Tig}, u_{Yig}) is independent of M_g, and $\zeta > 0$, then bivariate probit model can address self-selection of households into receiving remittances[22]. System of equations (2) corresponds to IV bivariate probit when the model is correctly specified. When bivariate Gaussian distribution assumption is not met, SNP model has been shown to perform better than IV bivariate probit model in consistent estimation of model parameters in system of equations (2) (De Luca, 2008).

IV 2SLS and IV bivariate probit models differ in the treatment effects they can estimate. IV 2SLS is only consistent in estimation of LATE; on the contrary, IV bivariate probit can recover consistent estimates of ATE, LATE and ATT[23] (Chiburis et al., 2011). When $\rho = 0$—that implies no self-selection into receiving treatment—, all treatment effects are equal, and IV

[22] The independence between latent errors and the instrument is needed to satisfy the independence of the instrument from potential outcomes and potential treatment indicators; and $\zeta > 0$ is needed to satisfy the first stage assumption. Greene (1998) has shown that the endogeneity of T_{jtg}^{*} does not affect the form of the likelihood functions; and thus, bivariate probit models are capable of recovering consistent coefficient estimates and treatment effects.

[23] The coefficient estimate of remittances in IV 2SLS directly provides LATE. ATE of remittances can be derived from the coefficient estimates of IV bivariate probit model as follows: $\hat{\Delta}_{ATE}^{IV\ BP} = \frac{1}{n}\sum_{i=1}^{n}[\Phi(\hat{\varphi} + \hat{\omega}_t + \hat{\xi} + X_{ijtg}'\hat{\gamma}_Y + Z_{jtg}'\hat{\eta}_Y + W_g'\hat{\theta}_Y) - \Phi(\hat{\varphi} + \hat{\omega}_t + X_{ijtg}'\hat{\gamma}_Y + Z_{jtg}'\hat{\eta}_Y + W_g'\hat{\theta}_Y)]$ where $\Phi(.)$ is standard normal cumulative distribution function. Chiburis et al. (2011) has shown that $\Delta_{LATE}^{IV\ 2SLS}$ and $\Delta_{ATE}^{IV\ BP}$ can be quite different when probability of treatment and probability of outcome are far from $\frac{1}{2}$ -which is the case for most of our estimations-, and the difference in estimates increase with ρ. Average marginal effect of remittances estimated by Stata postestimation command "margins, dydx(.)" after bivariate probit estimation actually recovers the ATE of remittances on outcomes of interest.

2SLS and IV bivariate probit estimates are comparable. However, we argue that the endogeneity bias might arise due to unobserved characteristics of households that may influence both their remitting behavior and schooling of their children, labor force participation of left behind family members, etc. Hence, the correlation coefficient ρ is most likely not equal to zero which makes it difficult to compare estimates from IV 2SLS and IV bivariate probit.

In addition to consistent estimation of remittance impact we also put much effort to achieve reliable statistical inference via accurate estimation of standard errors. To account for the fact that instrumental variable varies only at regional level and the individuals in a region are prone to receive the same shocks, we implement cluster robust standard error estimation. The consistency of the cluster robust standard error estimation relies on two assumptions: i) the number of clusters goes to infinity, and ii) clusters are homogeneous for which a sufficient condition is that the number of observations, the error covariance matrices, and the covariate matrices are the same for each cluster[24] (MacKinnon and Webb, 2017; Carter et al., 2017; Lee and Steigerwald, 2017). Cameron et al. (2008) has shown that when there are few clusters, cluster robust standard errors are downward biased and Wald tests based on cluster robust standard errors with standard normal critical values reject a true null hypothesis far too often[25]. Cameron and Miller (2015) suggest that few clusters may vary from less than 20 to less than 50 in balanced clusters, and may even be more than 50 in unbalanced clusters[26]. Angrist and Pischke (2008) suggest 42 clusters as large enough to achieve accurate statistical inference with cluster robust variance estimator. On the other hand, MacKinnon and Webb (2017) based on their simulation results argue that for wildly unbalanced clusters even 100 clusters may not be

[24] To elaborate on this point, let's stack all observations in a cluster and write the model as $Y_g = X_g\beta + u_g, g = 1,\dots,G$ where Y_g and u_g are $N_g x\ 1$, X_g is $N_g x\ k$, β is a k dimensional vector, and each cluster g contains N_g observations. Then, the accompanying cluster robust variance matrix estimator of $\hat{\beta}$ can be written as $\hat{V}_{cluster}\left(\hat{\beta}\right) = (X'X)^{-1}\{\sum_{g=1}^{G} X_g'\hat{u}_g\hat{u}_g'X_g\}(X'X)^{-1}$ where $\hat{u}_g$ is the N_g dimensional residual vector for cluster g. White (1984) proves that the Wald t statistic defined as $w = \frac{a'(\hat{\beta}-\beta_0)}{\sqrt{\widehat{Var}(a'\hat{\beta})}}$ under $H_0: a'\beta = a'\beta_0$,where a is a k dimensional selection vector with Euclidean norm $\|a\| = 1$, and the cluster robust variance component is $\widehat{Var}(a'\hat{\beta})$, is distributed standard normal and $\hat{V}_{cluster}\left(\hat{\beta}\right)$ is consistent for $V\left(\hat{\beta}\right)$ under three assumptions: 1) clusters are balanced -N_g does not vary over g-, 2) $E(X_g'u_gu_g'X_g)$ does not vary over g -an assumption also known as cluster homogeneity-, and 3) $G \to \infty$ as $n \to \infty$.

[25] The main issue is that for each cluster g the $N_g x\ N_g$ matrix $\hat{u}_g\hat{u}_g'$ is a poor estimate of the $N_g x\ N_g$ error covariance matrix $E(u_gu_g'|X_g)$. What makes $\hat{V}_{cluster}\left(\hat{\beta}\right)$ a reliable estimate for $V\left(\hat{\beta}\right)$ is based on an averaging over the number of clusters -as is made apparent by the summation indices in the formula of $\hat{V}_{cluster}\left(\hat{\beta}\right)$-, and with few clusters this averaging proves to be inadequate: results in high mean squared error for the cluster robust variance estimator, and consequently affects the empirical size of the cluster robust Wald t test (Carter et al., 2017). If the number of clusters goes to infinity, then it is appropriate to use standard normal critical values to conduct hypothesis testing. When there are few clusters, the distribution of w is unknown, and using standard normal distribution provides a poor approximation to the true distribution of Wald test statistic (Cameron and Miller, 2015). As an example, simulations run by Cameron et al. (2008) with 25 clusters suggest empirical test sizes that are almost two times of nominal size 0.05 when the Wald t statistic is based on cluster robust variance matrix estimate and is assumed to have standard normal distribution.

[26] Balanced clusters are of same size, and unbalanced clusters vary in the number of observations they have.

large enough for Wald tests to have right test sizes. Cameron et al. (2008) shows that unequal cluster sizes worsen the few clusters problem, and cluster robust standard error estimator, in that case, performs very poorly in terms of achieving empirical test sizes close to the nominal 5% size (i.e., the rejection frequencies of the Wald test with nominal size 0.05 is 0.129 for balanced clusters and 0.183 for unbalanced clusters where the number of clusters is set to 10). Carter et al. (2017) allows both unequal cluster sizes and cluster heterogeneity, and proves that cluster robust variance matrix estimate of OLS estimator $\left(\hat{V}_{cluster}\left(\hat{\beta}\right) = (X'X)^{-1}\{\sum_{g=1}^{G} X_g' \hat{u}_g \hat{u}_g' X_g\}(X'X)^{-1}\right)$ as defined in White (1984), is still consistent for $V\left(\hat{\beta}\right)$; and the Wald t statistic is asymptotically standard normal distributed. The behavior of the cluster robust t test is governed by a measure of cluster heterogeneity which depends on three sample specific statistics: cluster sizes N_g, observed covariate matrix X_g, and error covariance matrix $u_g u_g'$. Unless all clusters have the same number of observations, observed value of covariates, and error covariance matrix, assuming cluster homogeneity results in size distortion (Carter et al., 2017). The measure of cluster heterogeneity has been shown to reduce the actual number of clusters in order to produce *effective number of clusters* (G^*), and Carter et al. (2017) finds that when the effective number of clusters is low, the cluster robust variance estimator is downward biased and rejection rates of cluster robust t tests exceed the nominal size 0.05. Unless effective number of clusters is large, Carter et al. (2017) suggests implementing critical values that are larger than standard normal critical values[27]. Their study implies incorporating student-$t(G^*)$ critical values instead of standard normal critical values in hypothesis testing. MacKinnon and Webb (2017) run simulations allowing both the number of observations and covariates to vary across clusters, and show that tests based on $t(G-1)$ critical values[28] overreject and the rejection rates increase with the increase in either intra-cluster covariate correlation or intra-cluster error correlation, and tests based on $t(G^*-1)$ critical values greatly underreject and the rejection rates converge to zero when either intra-cluster covariate or error correlation converges to 1; and implementing $t(G^*)$ critical values in that case only slightly increases rejection rates. Their simulation results indicate that unequal cluster sizes and cluster heterogeneity render statistical inference with cluster robust standard errors unreliable: $t(G^*-1)$ critical values are too conservative and $t(G-1)$ critical values are not conservative enough.

[27] Lee and Steigerwald (2017) revisit Carter et al. (2017) study, and suggest 25 effective clusters as large enough to incorporate asymptotic theory and carry on hypothesis testing with standard normal critical values. Whenever effective number of clusters is less than 25, mistakenly applying standard normal critical values leads cluster robust Wald t tests to overreject a true null hypothesis.

[28] G refers to the observed number of clusters.

MacKinnon and Webb (2017) suggest implementing wild cluster bootstrap to recover critical values that brings rejection rates of Wald t tests close to the nominal size 0.05. Cameron et al. (2008) tests various bootstrap and non-bootstrap methods in a simulation study with few clusters and finds that null hypothesis imposed wild cluster bootstrap t procedure provides asymptotic refinement and does best among alternative methods when the clusters are unbalanced. MacKinnon and Webb (2017), and Cameron et al. (2008) agree on the strength of wild cluster bootstrap in recovering nominal test size when clusters are few and heterogenous. Our data set contains 26 unbalanced clusters (i.e., 26 regions with varying number of observations). In addition, covariate values vary across clusters[29]; thus, even if the cluster heterogeneity would have been modest in our case, it supposedly decreases effective number of clusters below 25, and arise the need for incorporating methods that would recover more conservative critical values. We follow Donald and Lang (2007) and Bester et al. (2011) in using $t(G-1)$ critical values to conduct Wald tests—based on cluster robust standard errors—for the remittance estimate being equal to zero. We additionally test with $t(G-2)$ critical values since Cameron et al. (2008) has shown that tests with $t(G-2)$ critical values improve rejection rates considerably. The degree of freedom adjustment refers to the constant and the clustered regressor of interest. Donald and Lang (2007) also propose using $t(G-L)$ distribution if the model in consideration has L explanatory variables that are invariant within cluster. In our study, to achieve the exogeneity of the instrument we make use of regional level covariates which are invariant within clusters; therefore, we follow their advice and perform tests with $t(G-L)$ critical values[30]. It is obvious that critical values from student's t distribution with varying degrees of freedom are larger than standard normal ones: with largest critical values obtained from $t(G-L)$ distribution and smallest critical values obtained from $t(G-1)$ distribution. Furthermore, we try to recover critical values larger than standard normal ones through null imposed wild cluster bootstrap t procedure[31]—will be referred as wild

[29] Plus, tests with heteroskedastic probit model rejects in most cases equally correlated errors assumption and, thus warn us about the possibility of error covariance matrix $u_g u_g'$ varying across regions, too.

[30] For any Wald test with critical values from t distribution with varying degrees of freedom, the symmetric p-value is presented.

[31] Consider a linear model with observations grouped in a cluster: $Y_g = X_g\beta + \varepsilon_g, g = 1,\ldots,G$, where Y_g and ε_g are $N_g x\ 1$, X_g is $N_g x\ k$, the matrix X has $N = \sum_{g=1}^{G} N_g$ rows, β is a k dimensional vector, and each cluster g contains N_g observations. We wish to test the null hypothesis that remittances have no impact on outcome. Without loss of generality, assume coefficient of remittances is β_1, so the null hypothesis is $H_0{:}\,\beta_1 = 0$. The cluster robust variance estimator of $\hat{\beta}$ is $\hat{V}_{cluster}\,(\hat{\beta}) = (X'X)^{-1}\{\sum_{g=1}^{G} X_g'\hat{\varepsilon}_g\hat{\varepsilon}_g'X_g\}(X'X)^{-1}$. To implement null restricted wild cluster bootstrap t procedure do the following steps: i) estimate the model above with OLS, and calculate cluster robust Wald t statistic (t_1) for $\beta_1 = 0$, using the square root of the first diagonal entry of $\hat{V}_{cluster}\,(\hat{\beta})$ as the denominator of t_1. ii) Re-estimate the model by fixing the coefficient of remittances at 0 (e.g. imposing $H_0{:}\,\beta_1 = 0$) in order to obtain restricted residuals $\tilde{\varepsilon}_g$ and restricted coefficient estimates $\tilde{\beta}$. iii) Using the bootstrap DGP as follows, for each bootstrap replication B, indexed by j, generate bootstrap dependent variables $\left(Y_{ig}^{*j}\right)_{j=1}^{B}$:

bootstrap hereafter—. Since we apply linear instrumental variable estimation and it is suspected that intra-cluster error correlation exists in the model, we implement a modified version of wild bootstrap by Davidson and MacKinnon (2010)—*wild restricted efficient residual bootstrap - WRE*—that can provide asymptotic refinement of a Wald test for the coefficient of the endogenous variable with a cluster robust variance estimator; that is to say, WRE yields asymptotically valid test for t statistic in the presence of heteroskedasticity of unknown form under the assumption of strong instruments. WRE differentiates from wild bootstrap in three ways: firstly, linear IV consists of estimating structural and reduced-form equations; thus, there are two disturbances that need to be bootstrapped; secondly, the null is imposed on the endogenous variable's coefficient in the structural equation; and lastly, the residuals from the reduced-form equation are augmented by the residuals from the restricted structural equation. To be more precise consider the two-equation model:

$$Y_{1g} = \beta Y_{2g} + Z_g\theta + u_{1g}, \quad g = 1, \ldots, G \tag{3}$$

$$Y_{2g} = W_g\gamma + u_{2g}, \;\; g = 1, \ldots, G \tag{4}$$

Here Y_{1g} and Y_{2g} stand for endogenous variables of dimension $N_g x\ 1$—Y_{2g} is the instrumented remittance variable in our context—, Z_g is an $N_g x\ k$ dimensional matrix of exogenous variables, W_g is an $N_g x\ l$ dimensional matrix of exogenous instruments and $l = k + 1$ so that the system is just identified, u_{1g} and u_{2g} are $N_g x\ 1$ matrices of disturbances. Equation (3) is a structural equation, and equation (4) is a reduced-form equation. The null hypothesis $\beta = 0$ is imposed on the structural equation; hence, the restricted residuals from the structural equation $(\tilde{u}_{1g})$ is obtained from a regression of $Y_1 = (Y_{11}'\ Y_{12}' \ldots Y_{1G}')'$ on $Z = (Z_1'\ Z_2' \ldots Z_G')'$ only. To obtain an efficient estimator of γ in equation (4), Davidson and MacKinnon (2010) suggest running the following regression:

$Y_{ig}^{*j} = X_{ig}\tilde{\beta} + \tilde{\varepsilon}_{ig}v_g^{*j}$ where sequence of i.i.d random variables $\left(v_g^{*j}\right)_{j=1}^{B}$ is independent of $(Y_{ig}, X_{ig})_{g=1}^{G}$ with $E\left(v_g^{*j}\right) = 0$ and $E\left(\left[v_g^{*j}\right]^2\right) = 1$, so that the product $\tilde{\varepsilon}_{ig}v_g^{*j}$ preserves the form of heteroskedasticity found in the original error terms ε_g. iv) For each bootstrap replication j, regress $Y^{*j} = (\left(Y_1^{*j}\right)' \left(Y_2^{*j}\right)' \ldots \left(Y_G^{*j}\right)')'$ on $X = (X_1'\ X_2' \ldots X_G')'$ and calculate t_1^{*j} using the square root of the first diagonal entry in $\hat{V}_{cluster}\left(\hat{\beta}\right)$ where bootstrap residuals from regressing Y^{*j} on X replace OLS residuals in the summation $\sum_{g=1}^{G} X_g'\hat{\varepsilon}_g\hat{\varepsilon}_g'X_g$. v) Calculate symmetric p-value for the Wald t statistic t_1, respectively as follows: $\hat{p}_s^* = \frac{1}{B}\sum_{j=1}^{B} I(\left| t_1^{*j}\right| > | t_1|)$, and reject the null hypothesis when $\hat{p}_s^* < \alpha$, where α is the size of the test. A key feature of wild bootstrap is that within a cluster, bootstrap errors of each observation depend on the same value of v_g^{*j}. Furthermore, unlike in nonparametric (pairs) bootstrap, wild bootstrap sets the covariate matrix X_g fixed across bootstrap replications. Rademacher and Mammen distributions are the two most common choices for v_g^{*j}. Davidson and Flachaire (2008) suggest using Rademacher weights when the disturbances have symmetric distribution. When the disturbances have asymmetric distribution, incorporating Mammen weights offer a skewness correction. Rademacher distribution puts probability one half to values 1 and -1. Mammen random variable equals $\frac{1-\sqrt{5}}{2}$ with probability $\frac{\sqrt{5}+1}{2\sqrt{5}}$, and equals $\frac{\sqrt{5}+1}{2}$ with probability $1 - \frac{\sqrt{5}+1}{2\sqrt{5}}$.

$$Y_2 = W\gamma + \vartheta M_z Y_1 + error \tag{5}$$

Where $Y_2 = (Y_{21}' \, Y_{22}' \dots Y_{2G}')'$, $W = (W_1' \, W_2' \dots W_G')'$, and M_z is the annihilator matrix producing the restricted residuals ($\tilde{u}_{1g}$) from the structural equation. $\hat{\gamma}$, and $\hat{\vartheta}$ are the coefficient estimates and the residuals in equation (5) that is augmented by $\tilde{u}_{1g}$ can be calculated as $\tilde{u}_2 = Y_2 - W\hat{\gamma}$ which is equal to the estimate of $error$ from equation (5) plus $\hat{\vartheta} M_z Y_1$.

$$\tilde{Y}_{1ig}^{*j} = \tilde{u}_{1ig}^{*j}, \qquad i = 1, \dots, N_g, \qquad g = 1, \dots, G \tag{6}$$

$$\tilde{Y}_{2ig}^{*j} = W_{ig}\hat{\gamma} + \tilde{u}_{2ig}^{*j}, \quad i = 1, \dots, N_g, \qquad g = 1, \dots, G \tag{7}$$

The bootstrap DGP uses equation (6) as the structural equation, and equation (7) as the reduced-form equation. Since the true value of θ does not have an influence on the t statistic for β, we can omit $Z_{ig}\hat{\theta}$ in equation (6) (Davidson and MacKinnon, 2010). The bootstrap errors for any bootstrap replication j are generated by

$$\begin{bmatrix} \tilde{u}_{1ig}^{*j} \\ \tilde{u}_{2ig}^{*j} \end{bmatrix} = \begin{bmatrix} \tilde{u}_{1ig} v_g^{*j} \\ \tilde{u}_{2ig} v_g^{*j} \end{bmatrix} \tag{8}$$

Where v_g^{*j} is a random variable independent of the data having either Rademacher or Mammen distribution as is in the wild bootstrap (see, e.g., Liu [1988], and Mammen [1993]). Davidson and Flachaire (2008) find out that whenever the residuals are not too asymmetrically distributed, it is better to use Rademacher distribution for the two-point random variable v_g^{*j}. Since IV estimation yields usually biased estimates of β, IV t statistics can have greater probability of rejecting in one direction than in the other one—the t statistic may have a non-symmetric distribution (Davidson and MacKinnon, 2010). Thus, we also present equal-tail bootstrap p-value of the Wald t statistic for $\beta = 0$ [32].

For nonlinear models, the wild bootstrap method is no longer available as nonlinear models lack conventional residuals (Cameron and Miller, 2015; Esarey and Menger, 2018). Kline and Santos (2012) develop a variant of wild bootstrap method—*score cluster bootstrap*—that can be employed in nonlinear models including models estimated by maximum likelihood such as probit and bivariate probit. Within our context, wild bootstrap can be viewed as a means of generating bootstrap residuals that preserves between clusters independence of and intra-cluster correlations of original error terms. Score cluster bootstrap, in accord with its name, generates bootstrap scores that preserve the heteroskedasticity present in the original scores (Kline and Santos, 2012). Score cluster bootstrap procedure includes: i) estimating the model

[32] $\hat{p}_{et}^{*} = 2\min\left(\frac{1}{B}\sum_{j=1}^{B} I(t_1^{*j} < t_1), \frac{1}{B}\sum_{j=1}^{B} I(t_1^{*j} > t_1)\right)$, and the null hypothesis is rejected when $\hat{p}_{et}^{*} < \alpha$.

once and obtaining the restricted individual score contributions—the restriction consists of the null hypothesis $H_0\colon \beta_1 = 0$ where β_1 is the coefficient on remittances—; ii) bootstrapping the restricted score contributions by weighting all individual scores in a given cluster with the same Rademacher or Mammen weights; iii) using the perturbed scores at each replication to build a set of Wald statistics, and approximating the true distribution of the Wald statistic with the bootstrapped Wald statistic distribution. Kline and Santos (2012) run simulations with a probit model and varying number of clusters (e.g., 5, 10, 20, 50, 200) to obtain empirical test sizes for Wald statistic using both the unrestricted and restricted score cluster bootstrap. Their results show that the restricted score cluster bootstrap outperforms the unrestricted counterpart in samples with less than or equal to 50 clusters for the model with normally distributed regressor of interest, and performs comparably with the unrestricted score bootstrap in samples with 20 or more clusters for the model with a heavily skewed regressor of interest, moreover, performs on par with pairs cluster bootstrap-t in large samples (samples with 50 or more clusters)[33]. For all sample sizes and for all probit models (with normally distributed or heavily skewed regressors), though, pairs cluster bootstrap-t performs moderately better than both restricted and unrestricted score cluster bootstrap and achieves to yield rejection rates close to nominal test size 0.05 [34]. Esarey and Menger (2018) simulation results with a probit model support findings of Kline and Santos (2012) on the performance of pairs cluster bootstrap-t. They find that pairs cluster bootstrap-t statistics have false positive rates near the nominal 0.05 value. For IV bivariate probit estimates of remittance coefficient, we present both symmetric and equal-tail restricted score cluster bootstrap p-value[35], and pairs cluster bootstrap-t p-value in addition to p-values from $t(G-1)$, $t(G-2)$, and $t(G-L)$ with cluster robust standard errors in the

[33] For the model $Y_g = X_g\beta + u_g,\ g = 1, \ldots, G$ where Y_g and u_g are $N_g x\ 1$, X_g is $N_g x\ k$, and β is a k dimensional vector of coefficients, pairs cluster bootstrap-t (percentile t bootstrap) procedure is implemented as follows: 1) For the original model, form the Wald t statistic $w = \frac{(\hat{\beta}_1 - \beta_0)}{se(\hat{\beta}_1)}$ where the null hypothesis is $H_0\colon \beta_1 = \beta_0$ and $se(\hat{\beta}_1)$ is the cluster robust standard error of $\hat{\beta}_1$—without loss of generality β_1 is the first row entry of parameter vector β—. 2) Draw with replacement G times from the original G clusters and form the bootstrap sample $\{(Y_1{}^*, X_1{}^*), (Y_2{}^*, X_2{}^*), \ldots, (Y_G{}^*, X_G{}^*)\}$ which consists of exactly G clusters, repeat this step B times. 3) Calculate the t statistic $w_b^* = \frac{(\hat{\beta}_{1,b}^* - \hat{\beta}_1)}{se(\hat{\beta}_{1,b}^*)}$ for the b[th] bootstrap replication by estimating the model using the b[th] bootstrap sample. $\hat{\beta}_{1,b}^*$ is the estimate of β_1, and $se(\hat{\beta}_{1,b}^*)$ is the cluster robust standard error of the estimate of β_1 from b[th] bootstrap replication, and Wald statistic is centered on the estimate of β_1 from the original sample as the bootstrap considers the sample as the population. 4) Let $w_{(1)}^*, w_{(2)}^*, \ldots, w_{(B)}^*$ be an ascending ordering of bootstrap Wald t statistics which is argued to trace out the density of Wald test by replacing the normal approximation (Cameron and Miller, 2015). The symmetric p-value of the Wald test is the proportion of times that $|w| < |w_b^*|$ for $b = 1,2, \ldots, B$, or in other words $\hat{p}_s^* = \frac{1}{B}\sum_{j=1}^{B} I(|\ w_b^*| > |\ w|)$, and we reject the null when $\hat{p}_s^* < \alpha$.

[34] Rejection rates of pairs cluster bootstrap-t procedure vary from 0.048 to 0.060 for a test size of 0.05.

[35] Each test is performed separately with both Rademacher and Mammen weights.

denominator of the t statistic[36]. When α is the size of the test, Davidson and MacKinnon (2010) advice $\alpha(B+1)$ to be an integer where B is the number of bootstrap replications. For wild restricted efficient residual bootstrap and score cluster bootstrap, we choose $\alpha = 9{,}999$; while for pairs cluster bootstrap-t we choose $\alpha = 1{,}999$ [37]. Since wild restricted efficient residual bootstrap runs linear regressions and score cluster bootstrap estimates the model only once, they took considerably less time compared to pairs cluster bootstrap-t in which the model is estimated repeatedly at each bootstrap replication.

Moulton (1986) approximates the difference between default OLS standard errors based on $s^2(X'X)^{-1}$ and cluster robust standard errors with unbalanced clusters for a regressor (without loss of generality let's take k[th] regressor, in our case it is the remittances) by inflation factor $\tau_k \cong \sqrt{1+\rho_{x_k}\rho_u(\left(\frac{V[N_g]}{\bar{N}_g}\right)+\bar{N}_g-1)}$ [38]. ρ_{x_k} represents the within cluster correlation of k[th] regressor x_{igk}, ρ_u is a measure of the within cluster error correlation, $\bar{N}_g$ is the average cluster size and $V\left[N_g\right]$ is the variance of cluster size with $g = 1, \ldots, G$. To decrease efficiency losses and to avoid degrading of the performance of Wald tests with $t(.)$ critical values, we restrict our estimation samples to include only the oldest observation in a household for the age category under consideration[39] (e.g., 6-14, or 15-19). Allowing other household members to enter the sample will most likely increase within cluster regressor correlation ($Cor\left(x_{igk}, x_{jgk}\right)$ for $i \neq j$) and within cluster error correlation as individuals in a household living in the same region have the same remittance receiving status and tend to receive the same unobserved shocks. We also want to intentionally minimize the difference between standard OLS standard errors and cluster robust standard errors for remittance coefficient estimate due to the fact that SNP estimation does not allow for cluster robust standard error estimation. Including more than one observation from households where possible would further increase the average cluster size as well as possibly increasing within cluster error and within cluster regressor correlation. This would result in hypothetically larger cluster robust standard errors for remittances that we couldn't manage to estimate and consequently, in elevated concern for the reliability of

[36] Wild restricted efficient residual bootstrap and score cluster bootstrap was implemented in Stata by *boottest* command by David Roodman.

[37] Cameron and Miller (2015) suggest 999 bootstrap replications as enough to trace out the true distribution of the Wald t statistic via wild cluster bootstrap or pairs cluster bootstrap-t.

[38] This approximation assumes equicorrelated errors within clusters: $Cor\left(u_{ig}, u_{jg}\right) = \rho$ for all $i \neq j$ and for each g, and number of clusters going to infinity. Cluster robust standard error of $\hat{\beta}_k$ is approximately τ_k times larger than its standard OLS standard error.

[39] MacKinnon and Webb (2017) find out that the performance of Wald tests with t(G-1) critical values deteriorate with the increase in either within cluster regressor or within cluster error correlation.

statistical inference with the SNP estimation. For 6-14 years old girls, the average cluster size would have increased by 311 from a base level of 929 which is almost 33% increase in the average cluster size if the estimation samples would have contained sisters. For 6-14 years old boys, the increase in the average cluster size is 293 from a base level of 978 which is almost a 30% increase if the estimation samples would have included brothers. The multipliers ρ_{x_k} and ρ_u in Moulton's correction formula would have increased too, which in total would have created an enormous difference between standard errors estimated with SNP model and standard errors that should have been estimated to account for intra-cluster dependency of observations[40]. It is possible to estimate cluster robust variance matrix of $\hat{\beta}$ within SNP estimation through pairs cluster bootstrap-se procedure[41]. Pairs cluster bootstrap-se variance estimates and traditional cluster robust variance estimates are asymptotically equivalent; however, around 400 bootstrap replications is suggested to achieve consistent estimation of $Var(\hat{\beta})$. However, due to time constraints this is infeasible[42] (Cameron and Miller, 2015).

Pooled cross-sectional nature of the data introduces the time dimension that may require the standard errors to be clustered besides region. If individuals receive shocks that are correlated within years but independent across years, then standard errors should account for that and be clustered both by regions and years. We assume that all individuals in a year receive the same shocks, and no event has occurred that we know of between 2003 and 2011 that influence individuals from a given year differently based on their characteristics such as the regions they live in, educational attainment they have, etc. Therefore, we include year fixed effects in our estimation models that absorb the within year clustering, and one-way clustering on regions suffice to have reliable inference (Cameron and Miller, 2015).

Our results present coefficient estimates of remittances, and additionally for school attendance and labor supply estimations of children between 15-19 years of age present

[40] Intuitively, when the data has a group structure, any new observation does not bring out a new piece of information as in the case of i.i.d observations. Including units that have correlated errors and correlated regressors with the pre-existing observations would have simply contributed to the impreciseness of the estimation.

[41] For the model $Y_g = X_g\beta + u_g,\ g = 1,\dots,G$ where Y_g and u_g are $N_g x\ 1$, X_g is $N_g x\ k$, and β is a k dimensional vector of coefficients, pairs cluster bootstrap-se procedure is implemented as follows : (1) Resample the clusters with replacement G times from the original clusters and form G clusters $\{(Y_1^*, X_1^*), (Y_2^*, X_2^*), \dots, (Y_G^*, X_G^*)\}$ (2) Repeat first step B times. (3) At each replication estimate β, for b[th] bootstrap sample the estimate of β is denoted by $\hat{\beta}_b$. (4) use B estimates of β; $\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_B$ to estimate the variance matrix of estimates as $\hat{V}_{cluster,boot}\ (\hat{\beta}) = \frac{1}{B-1}\sum_{i=1}^{B}(\hat{\beta}_i - \overline{\hat{\beta}})(\hat{\beta}_i - \overline{\hat{\beta}})'$ where $\overline{\hat{\beta}} = \frac{1}{B}\sum_{i=1}^{B}\hat{\beta}_i$, and cluster robust standard errors are obtained by taking the square root of the diagonal entries in $\hat{V}_{cluster,boot}\ (\hat{\beta})$. It is important to have the bootstrap over the clusters and not over the individuals. Each bootstrap sample contains exactly G clusters where some of the clusters from the original data may not appear in the bootstrap resample and some other clusters may appear more than once.

[42] The semi-parametric estimation of the model is computationally demanding with each estimation of SNP model taking around 6 to 8 hours.

coefficient estimates of a dummy variable that captures whether a child is affected by the educational system reform that took place simultaneously across all regions in Turkey in 1997-1998 education year. The coefficient estimates do not recover treatment effects except for IV 2SLS, but points to the direction of the treatment effect—whether it has a positive or negative impact on outcome. Although SNP estimation is a direct extension of bivariate probit, IV bivariate probit and SNP coefficient estimates are not comparable due to a scale difference between variances of error terms[43]. There are two ways to take into account the differences in the scale of error terms: one is to compare the ratio of estimated coefficients by using Stata's "*nlcom*" command, and the other is to compare estimates of marginal effects of remittances. We prefer the latter one and present average marginal effects of remittances from IV bivariate probit and SNP models in Table 1-25.

1.3 Data and Summary Statistics

1.3.1 Data and Sample Definition

This paper uses data from cross-sectional household budget surveys, "Hanehalkı Bütçe Anketi" conducted by Turkey's national statistical agency (Türkiye İstatistik Kurumu). To construct the data, we pool nine waves of the household budget surveys including the years between 2003 and 2011. Each wave of the survey is representative at urban, rural and national levels. The surveys contain information on demographic characteristics in addition to socioeconomic indicators such as the last finished schooling level, current and previous employment status, earnings both in cash and in-kind, expenditures, and transfers received from abroad (remittances). The data set has 395,117 observations from 98,568 households.

Concerning remittances, the survey questions include the amount of remittances received by household members in the last 12 months. Transfers from abroad to any household member consist of 3 categories: pension benefit, in-kind income, and cash receipts from spouses, friends, or relatives. If at least one member of a household reports receiving nonzero value of remittances of any sort, then the household is called a remittance receiving household. If none of the members of a household receives remittances, then the corresponding household is considered a non-receiving household. As explained in section 1.2.1, we include households that receive pension benefits from host countries to capture past migration experience. Even though the amount of remittances a household receives is reported in our data, for the reasons

[43] Bivariate probit model assumes latent errors to have bivariate Gaussian distribution with zero means, unit variances and correlation coefficient ρ. SNP model does not require latent errors to have unit variances (De Luca, 2008).

explained in section 1.2.1 and for the possibility of having measurement errors in the amount of remittances due to households' tendency in pooling income from labor and non-labor sources which results in recall bias when remittances are reported, we instead use an identifier for the remittance receipt status of a household. There are 1,529 households out of 98,568 that receives remittances in our data set. This corresponds to a share of 0.015. In other words, out of every 1,000 households, 15 of them receive remittances. This ratio is considerably lower than the share of migrant households (0.22) in McKenzie and Rapoport (2011), the share of remittance receiving households (0.19) in Acosta (2011), and the proportion of migrant households (0.076) in Cox-Edwards and Rodriguez-Oreggia (2009), and is the main reason for the linear instrumental variable estimation producing treatment effects and predicted outcomes out of the unit interval.

The analysis regarding child human capital accumulation outcomes focuses on children between ages 6 and 19. The analyses are carried out separately for boys and girls. In addition, the age range is divided into two categories, ages between 6 and 14, and ages between 15 and 19. The particular choice of age groups has intrinsic importance because in Turkey, primary and lower secondary education became mandatory with the 1997-1998 education year which covers the ages 6 and 14. Prior to the 1997 education reform, a student in Turkish education system followed the following successive steps: compulsory primary education (5 years), lower secondary education (3 years), upper secondary education (3 years), and higher education (university education). Turkey implemented an education system reform in 1997 which extended the duration of compulsory schooling from 5 to 8 years[44] by combining and redefining primary and lower secondary education as compulsory schooling. This education reform took effect simultaneously in each part of the country. In addition, the education reform was unexpected in the sense that the date of the reform did not coincide with the macroeconomic developments in the country (Aydemir and Kırdar, 2015). The education reform affected children who at the end of 1996-1997 education year have finished grade 4 or lower, and forced them to stay in school till they graduate from lower secondary school. Children who have finished grade 5 at the end of 1996-1997 education year were not affected by the education reform. Children generally start school at 6 years old in Turkey; hence, those born in 1987 or later are affected by the education reform[45] (Aydemir and Kırdar, 2015). In our data set, the

[44] 5.1.1961 *tarih ve* 222 *Sayılı İlköğretim ve Eğitim Kanunu 2.Maddesi.*

[45] 07.08.1992 *Cuma tarihli* 21308 *Sayılı T.C. Resmi Gazete*: For a given year, children who are going to be 72 months old at the end of December have the right to start school in that year. A child has to be at least $5\frac{2}{3}$ years old in September to begin school in that year. So, a birth cohort always begins school at the same year. However, children who are physically undeveloped but are supposed to start school in a given year can delay starting school one year with the formal request of their parents.

birth year of an individual can be obtained by subtracting the reported age from the survey year. We create a dummy variable taking value one if a child is born in 1987 or later, and takes value zero otherwise. This variable is included in child human capital investment regressions and captures the impact of the education reform on schooling and labor supply of children aged 15- to 19-years-old. All children aged 6 to 14 in our sample are subject to the education reform. Thus, there is no variation in schooling attainment due to the different exposure to education reform for this age group. On the other hand, for children between ages 15 and 19 there is variation in the education reform dummy for the years 2003, 2004 and 2005. In 2003, children aged 15 and 16; in 2004, children aged 15, 16 and 17; in 2005, children aged 15, 16, 17, and 18 were affected by the education reform. After 2005, all children aged 15 to 19 were supposed to comply with the education reform. Children between 15 and 19 years old generally go to high school in Turkey (upper secondary education). Therefore, by controlling for the education reform in child schooling regressions what we aim to capture is the spillover effect of the education reform to further one's education beyond the lower secondary school. Aydemir and Kırdar (2015) show that the spillover effect for high school continuation is more pronounced for females than males. Aydemir and Kırdar (2015) also state that there is no spillover effect of the education reform for university education. Although it would have been nice to see whether findings of Aydemir and Kırdar (2015) hold in our sample on the spillover effect of the education reform for university education, we are unable to construct the education reform dummy for the years between 2007 and 2010 in which there is variation in education reform dummy of individuals aged 20 to 24 who are supposed to be attending university[46].

In principal, education services for primary and lower secondary education (grades 1 through 8) are provided for free by the Ministry of National Education. It is expected to observe high rates of school attendance for both boys and girls between ages 6 and 14. Therefore, remittances are not expected to be a significant determinant of school attendance due to the free of charge provision of education services and its mandatory feature. Child labor which is an important aspect of human capital accumulation is observed in the data from the beginning of age 15. Below this age, there is no information about whether a child is in labor force or not. Since labor force participation of a child reduces the time available for schooling, child labor adversely affects school attendance. Moreover, upper secondary education is not obligatory in

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Children born in 1987 (and later) can start school in 1993 (and afterwards) and have finished grade 4 (or lower) at the end of 1996-1997 education year; hence were the subjects of the education reform.

[46] In our data, the age variable is reported seprately for each age only for years 2003, 2004, 2005, and 2011, and for the remaining years it is reported in groups.

Turkey. Children have the freedom to leave school and take part in other activities, such as labor. For this specific age group, remittances may play an important role in keeping children out of work and in school, especially for children in low income families.

The samples for child human capital accumulation outcomes are restricted to children who are sons or daughters of the household head[47]. This helps ensure that investigation of the impacts of remittances is on children for whom the parents and not someone else make decisions about the children's schooling and labor force participation. Furthermore, from each given household with children between the ages 6 and 19, we take only the oldest child in the corresponding age category for the reasons explained in section 1.2.2. The resulting samples include 78,761 children between ages 6 and 19 from 50,137 households[48].

Following the practice in the literature we cover a broad interval of ages to estimate the impacts of remittances on adult labor force participation decisions[49]. Our analysis includes three age categories for men and women: 20-24, 24-49, and 50-64. Individuals between ages 20 and 24 may still receive some education; and thus, we consider them as a separate group from prime-age working individuals. Our second group consists of prime-age men and women[50], and the last group includes elderly citizens. We again take the oldest individual in the corresponding age group in a household as the unit of observation for our analysis. Also, our setup selects the household head as the unit of observation for any age group if the household head is in the age interval under consideration. This is something desired as what we want to learn is the impact of remittances on employment patterns for individuals closely related to the household head—either the household head or the spouse of the household head—instead of other relatives of the household head for whom the remittances may not have an influence on employment

[47] There are 129 remittance receiving households where the household head is a grandparent of the children aged 6 to 19 (extended families). These households do not include any child of the household head belonging to the corresponding age groups 6-14 and 15-19. We exclude children from these households in our regressions because it is not possible to identify their parents, and there is no way to learn about their parents' background characteristics. Furthermore, including these households would most likely bring up sample selection issues as household budget surveys do not present information about households that have emigrated as a whole. Separate estimations for children living in extended families may provide more insights for the impacts of remittances; though, small sample sizes make it extremely difficult to estimate treatment effects (i.e., there are 11 remittance receiving households with a granddaughter aged 15 to 19, and the corresponding figure for non-recipient households is 638).

[48] One of the households have missing information about the remittance receipt status, and hence omitted from analysis yielding a sample size of 78,759 from 50,136 households.

[49] Acosta (2006) considers males and females aged 22 to 65; Binzel and Assaad (2011) restrict analysis to prime-age women aged 20 to 49; Cox-Edwards and Rodriguez-Oreggia (2009) include in their analysis men and women aged 12 to 65; Amuedo-Dorantes and Pozo (2006) restrict their sample to men and women between ages 16 and 64; Lokshin and Glinskaya (2009) investigate the impacts of male migration on left behind prime-age women with ages between 18 and 60.

[50] Since early retirement for individuals at the end of 40s is a possibility in Turkey, we do not consider ages 50 to 54 as a part of prime-age.

probabilities[51]. Household heads may have responsibilities different than the ones of the other family members such as satisfying the basic needs of the family by providing food, clothing and shelter, or looking after children and taking care of the chores, hence being a household head may have an influence on employment patterns. We control for being the household head by means of a dummy variable which takes the value one if the observation is the household head and zero otherwise[52]. The adult labor force participation regressions include 208,447 observations from 92,894 households[53].

Lastly, to assess the impact of remittances on household well-being we implement definitions of poverty based on the distribution of households' adult equivalent yearly disposable income and the distribution of households' adult equivalent monthly expenditure amounts (both relative poverty definitions are by TÜİK), and international measures of poverty defined as households' adult equivalent daily expenditure amounts of 1$, 2.15$, and 4.30$. The samples include 98,567 households. One of the households reports missing value for remittance receipt status and therefore is omitted from the analysis.

1.3.2 Descriptive Statistics

We present four tables to summarize the key variables in our analysis. The first table presents the distribution of remittance receipts, amount remitted and corresponding shares of cash, in-kind and pension benefits in the amount remitted. According to our data, 1.37% of the population live in households that receive remittances. The likelihood for households to receive remittances increases with household income which may be rationalized by the hypothesis that sending a family member abroad and receiving remittances in return is costly, and liquidity constraints become less binding with the increase in income that makes high income families more able to finance migration of a member and more likely to receive remittances. Recipient households mostly reside in urban areas, and Central Anatolia accounts for the highest share of

[51] 33,6% of recipient households are female headed. Among recipient households with a missing male spouse all except one are female headed, and among remittance receiving households with a male head, 80% of the women included in our analysis are spouses of household head. For non-recipient households, 11% are female headed. For non-recipient households with a female head, our samples identify 78% of household heads, and for non-recipient households with a male head, our samples identify 89% of spouses of household heads. We exclude women aged 20 to 24 in calculating the corresponding shares as for remittance receiving households 71% of women (ages 20-24 years) live with their parents or grandparents, and since the impact of remittances on labor force participation may vary with the role in the household (spouse, child, etc.) we estimate separate regressions for women aged 20 to 24 who live with their parents.

[52] There is a significant difference between recipient and non-recipient households in the share of women household heads (ages 25-64 years). For recipient households 29% of women aged 25 to 64 are household heads, and for non-recipient households the corresponding share is 0,08. In labor force participation regressions of females, the household head and the receipt of remittances may be simultaneously determined. This may result in finding biased estimates for the coefficient of household head.

[53] One household with missing information about remittance receipt status is omitted from the analysis yielding a total of 208,445 observations from 92,893 households.

recipient households among the seven geographical regions of Turkey. Central Anatolia, Marmara and Mediterranean, combined, account for more than 60% of recipient households. On average recipient households received remittances amounting 5,062 TL per adult per year[54]. Remitted amount increases monotonically with household income. There is a substantial difference in the average amount remitted for the richest quintile and the remaining four quintiles: the average amount remitted for the richest quintile is more than double the average amount remitted for the fourth quintile. Eastern part of the country, on average, receive less remittances compared to other parts of the country. Black Sea region, although accounting for the third smallest share of recipient households, receive on average the highest amount of remittances among all regions. The fourth column in Table 1-1 shows that the contribution of remittances in household income decreases as household income increases. However, the richest quintile breaks the pattern: the contribution of remittances is highest for the richest quintile. Our data suggests a channel for this observation. Column 6 of Table 1-1 points to an enormous difference in pension benefit share of remittances between the richest quintile and the remaining quintiles. In addition, the average pension benefit for the richest quintile is more than 4 times larger than the corresponding value for the fourth quintile. These combined with the number of foreign retirees for the richest quintile being more than double the corresponding number for the fourth quintile result in household income share of remittances for the richest quintile exceeding the contribution of remittances to household income in remaining quintiles. For recipient households, the average remittance share of household income is 41%; with cash receipts, retirement pensions and in-kind receipts constituting 63%, 28%, and 8% of remittances, respectively.

Table 1-2 shows the main characteristics of households with children aged 6-19, and of the regions the children live in, plus the summary statistics of the children's outcome variables, all categorized by the remittance receipt status[55]. Regarding the outcome variables, 6-19-years-old boys in recipient households are more likely to attend school compared to their non-recipient counterparts. The situation is the same for 6-19-years-old girls but the gap in average school attendance rates for recipient and non-recipient households is smaller compared to the corresponding difference in the male sample. A lower proportion of recipient boys and girls aged 6-14 are illiterate. 15-19-years-old girls from recipient households are less likely to take

[54] To have comparable TL figures across households, we inflate prices to December 2011 using TÜİK's consumer price index. To calculate adult equivalent household size, we use modified version of OECD's equivalence scale which counts the first adult in the household as 1, the remaining members older than 14 as 0.5 and younger than 14 as 0.3.

[55] There are two restrictions for a child to be in the sample: he/she needs to be the child of the household head and needs to be the oldest child in the household in corresponding age groups: 6-14 or 15-19.

part in market labor force, and are less likely to work for wage or as unpaid family workers[56]. There is no variation in self-employment for recipient girls aged 15 to 19 which brings about some serious estimation problems in identifying the remittance impact on girls' likelihood to be self-employed. A lower proportion of boys aged 15-19 from recipient households participate in labor force or work as unpaid family workers. On the other hand, the share of wage workers for 15-19-years-old boys is slightly larger for recipient households.

Other differences concerning recipient and non-recipient 6-19-years-old children are associated with their household and region characteristics. As expected, recipient households have a smaller number of adult equivalent members[57], fewer children aged 0-5 and 6-19, and fewer 20-64-years-old working age adults. Recipient households have a higher proportion of female household heads compared to non-recipient households with the difference in shares of female head coming close to 34 percentage points. On average, the adult equivalent yearly disposable income is almost 400 TL less for recipient households. Children from recipient households have parents with a lower educational attainment, measured by the last finished schooling level, which is consistent with the lower average income figures for recipient households. Another important difference in household characteristics is the higher share of rural settlement for recipient households[58].

Children from recipient households live in regions with a higher historical migration rate. This observation lays the ground for regional historical migration network to be a relevant instrument for households' remittance recipient status. The evidence on regional characteristics suggest that recipient households are located in historically less developed regions. Gross enrollment ratios, both historically and contemporaneous, are equivalent for recipient and non-recipient households. The shares of 25- to 64-years-old males in a region with varying educational attainment do not change much with respect to remittance receipt status of households. Lastly, recipient households are located in regions with a more pronounced agricultural employment rate for 15-64-years-old males, and with a higher unemployment ratio for 15-64-years-old males.

Table 1-3 presents the summary statistics for the adult sample defined in section 1.3.1. With regard to labor force participation outcome variables, males from recipient households

[56] The survey questions on employment patterns of individuals are aimed to bring about the main job done in the last 4 weeks prior to the interview.

[57] For children from recipient households 42% of them have a parent absent at the household at the survey date. For children from non-recipient households this share is only 6%.

[58] Settlements with population less than 20,000 are defined as rural, and settlements with population equal to or larger than 20,001 are defined as urban.

regardless of their age and the kind of work in consideration have lower participation rate compared to their non-recipient counterparts. Only exception is the higher take up of unpaid family work by prime-age males from recipient households with the gap in unpaid family work shares reaching 1.5 percentage points. Even though deducing any kind of causality from this observation is not possible, it may still direct the attention to the income effect of remittances for the left behind male household members. 20-24-years-old and prime-age women from recipient households are less likely to work for wage and more likely to work as self-employed. In addition, 20-24-years-old females from recipient households have a higher share of non-wage workers (i.e., females who are either self-employed or work as unpaid family worker) compared to their non-recipient counterparts. For elder women, the share of self-employed females is higher for recipient households. Hence, women from recipient households irrespective of their age are more frequently observed to be self-employed. Prime-age and elder females are less likely to participate in labor force whereas the situation is reversed for 20-24-years old women. These observations about labor supply behaviors of females may suggest both an income effect of remittances and substitution effect of migration which results from the absence of the migrant member and from productive uses of remittances in household enterprises. Regarding individual characteristics, adults from recipient households appear to be less educated, less likely to be married and more likely to be household heads compared to adults from non-recipient households. Differences in adults' household characteristics include; a higher share of rural settlement, better access to water services, a smaller adult equivalent household size, fewer children and adults for recipient households. Recipient households also have lower chance of including highly educated members. Recipient households are more likely to be located in regions with a higher historical migration prevalence. Though, these regions also appear to be historically less developed. Other regional characteristics do not vary much with the remittance receipt status of adults.

Table 1-4 presents summary statistics for households categorized by remittance receipt status. Contrary to the earlier descriptive statistics, the unit of observation is households in Table 1-4. Regarding the main variable of interest, 1.55% of households receive remittances, and recipient households seem to be doing better with respect to household well-being measures compared to non-recipient households. A lower share of recipient households has per adult equivalent yearly disposable income below various proportions of the median of the per adult equivalent yearly disposable household income distribution. Moreover, a higher share of recipient households manages to be located relatively better in the per adult equivalent monthly household expenditure distribution. None of the recipient households and only 10 of the non-recipient households live under daily per adult equivalent 1$ cutoff which causes models regarding this dependent variable being inestimable. A higher proportion of recipient households has maximum educational attainment equal to junior high or below, and a lower proportion of recipient households has maximum educational attainment equal to high school or above. Household heads of recipient households appear to be older, less likely to be married, and more likely to be female. Recipient households appear to earn more income on yearly basis and spend more on monthly basis which is consistent with recipient households being better off with respect to poverty indicators. Recipient households have a lower number of adult equivalent members, fewer children (aged 6-19) and adults, better access to water services, a lower share of natural gas system ownership, and more chance of living in rural areas. Regarding the regional level variables, the pattern in earlier descriptive statistics preserves in Table 1-4: recipient households appear to live in regions with a higher historical migration rate, a lower historical development level, a more pronounced unemployment rate, and an agriculture dense sector.

1.4 Results

We begin this section by presenting results for the likelihood of receiving remittances. We run first stage regressions for samples of children aged 6-14 and 15-19; adults aged 20-24, 25-49 and 50-64; and households. These samples constitute of the observations for which we aim to find the impact of remittances on various outcomes. For each age group, we run separate first stage regressions for males and females.

Secondly, we estimate the impact of remittances on child human capital accumulation, child labor, adult labor force participation and household well-being, respectively. For each outcome, we present the coefficient estimate of remittances from parametric non-IV probit model, parametric IV 2SLS and IV bivariate probit models, and semiparametric IV SNP model. The reason for reporting coefficient estimates rather than treatment effects is to address problems in accurate standard error estimation when the model errors are correlated within cluster and the number of clusters is few. We estimate both White heteroskedasticity robust standard errors and cluster robust standard errors for remittances to gauge the importance of caring about the grouped nature of the observations. Since the data is grouped into 26 clusters, we pay much attention to recover nominal test sizes by applying various methods that have been shown to provide asymptotic refinement for Wald test (of remittance coefficient estimate being equal to zero) including: hypothesis testing with $t(G-1)$, $t(G-2)$, and $t(G-L)$ critical values, wild bootstrap (*wild restricted efficient residual bootstrap* of Davidson and

MacKinnon [2010]) symmetric and equal-tail Wald test for IV 2SLS estimations (calculated with both Rademacher and Mammen weights), null restricted score bootstrap symmetric and equal-tail Wald test (calculated with both Rademacher and Mammen weights) for non-IV probit and IV bivariate probit regressions, plus pairs cluster bootstrap-t procedure for IV bivariate probit regressions.

Lastly, to be able to compare treatment effects from parametric non-IV probit, parametric IV bivariate probit, and semiparametric IV SNP models, we estimate average marginal effects of remittances. As mentioned before, estimates of average marginal effects are not affected by the scale difference in error variances and thus are comparable. Estimates of average marginal effects from these models correspond to estimates of average treatment effect of remittances. We report LATE of remittances from IV 2SLS models besides average marginal effects from nonlinear models to see the extent of change in the average effect of remittances for compliers and the entire population.

1.4.1 Determinants of remittances

We estimate both a linear probability model and a nonlinear probit specification for determinants of remittances; the latter is to account for the binary nature of the dependent variable. To assess the relevance of the continuously distributed instrument, we report: p-value of the Wald test for instrument's coefficient estimate if the first stage regression is nonlinear; and *effective F statistic* (Olea and Pflueger, 2013) for the coefficient estimate of the instrument whenever the first stage is instead a linear probability model. Effective F statistic, by adjusting the first stage non-robust F statistic, accounts for violations of i.i.d model errors assumption through heteroskedasticity, serial correlation and/or clustering. Effective F statistic is equivalent to robust F statistic (a.k.a Kleibergen-Paap rk Wald F statistic) in just identified 2SLS and LIML models and differs in overidentified case. Cluster robust standard errors for coefficient estimates are reported in parenthesis. While estimating cluster robust standard errors, small sample modifications have been applied to reduce the downward bias in the standard errors resulting from finite number of clusters[59].

[59] The small sample correction includes multiplication of cluster specific residuals $(\hat{\varepsilon}_g)$ with a scalar equal to $\sqrt{\frac{G}{G-1}\frac{N-1}{N-K}}$ in the formula for cluster robust variance estimator of $\hat{\beta}$: $\hat{V}_{cluster}\,(\hat{\beta}) = (X'X)^{-1}\{\sum_{g=1}^{G} X_g'\hat{\varepsilon}_g\hat{\varepsilon}_g'X_g\}(X'X)^{-1}$ where G is the number of clusters, N is the number of observations, and K is the number of regressors, and using t(G-1) distribution in calculating p-values of Wald tests in linear models—we use *ivreg2* command in Stata to run the first stage regression of IV 2SLS—. For probit models, as small sample correction Stata only inflates cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ and uses standard normal distribution in calculating p-values. The small sample modifications result in an increase both in standard errors and in p-values.

Table 1-5 presents first stage results (coefficient estimates) for samples of children between ages 6 and 19 years old. The dependent variable is a dummy variable indicating the remittance receipt status of the household that the child belongs to. To begin with, the first stage results from IV 2SLS and probit regressions of determinants of remittances are in line with respect to the direction and statistical significance of the impacts. The absence of information about the remittance sender which is likely to influence the decision to remit makes it difficult to attach causal interpretation to the estimates, i.e., the schooling outcomes of the household head may be correlated with the schooling outcomes of the sender, especially under assortative mating assumption and for households in which the head is the spouse of the sender. The first stage regressions are best interpreted as identifying variables for households that can explain selection into receiving remittances. The results suggest that, regardless of age and gender of the child, as the educational attainment of the parent increases, the likelihood for the household to receive remittances decreases which is consistent with high earnings potential for highly educated individuals reducing the need for a member to migrate and send remittances to support the family. Households with older heads are more likely to receive remittances, but this impact is insignificant for 6-14-years-old boys and the reverse of the relation is true for 6-14-years-old girls; although the estimates are only marginally significant for younger girls. Households with married heads have higher chances of receiving remittances. Ownership of natural gas system, which is considered as an attribute of the house, has opposing impacts for the likelihood of receiving remittances for younger and older boys. For the samples of older children, as the number of school age children (ages 6-19 years old) increases, the probability of receiving remittances for the households they belong to decreases. An increase in the number of working age males (ages 20-64 years old) in a household influences the incidence of remittance receipt adversely. An increase in the number of adult males may imply an increase in earnings potential for the family, which in return may decrease the need for the family to rely on remittances. An increase in the number of adult females, though increases the likelihood of receiving remittances for samples of 6-14-years old children. The increase in the number of adult females may increase the dependency ratio and may inflate the need to have higher income for which one of the channels may be to send a migrant and receive remittances in return. The region level estimates suggest that remittance receipts are more frequent in historically underdeveloped regions. As regions' development levels and emigration frequencies were negatively correlated in the past (Ayhan et al., 2000) and the initial mass emigration from regions helped create the migrant networks that are predictive of current migration flows and remittance receipts, the historical regional development level variable is most likely to capture some part of the variation in historical migration network. The collinearity between historical development levels and migrant networks, in return, may prevent precise estimation of the coefficient estimate of migrant networks in first stage regression, and eventually leads to a decrease in the predictive power of the instrument. In section 1.2.1, we argue that some other regional level covariates should also be controlled for in the structural and reduced-form equations to have a valid instrument. However, the inclusion of other regional level covariates in the first stage would further decrease the predictive power of the instrument (further decreases the effective F statistic of the instrument). Nevertheless, our first stage results show that except for one specification (15-19-years-old females) the instrument proves to be strong. Unemployment rate of a region is a significant determinant of remittance receipts with more unemployment inducing more occurrences of remittances. Share of men in a region working in agriculture is positively associated with the remittance receipts. Households from years 2008, 2009 and 2010 are also more likely to receive remittances. Last two findings may suggest that as economic risks increase in an environment, remittances may serve the function of insurance mechanisms (Yang and Choi, 2005). The historical migration rate by region proves to be a relevant instrumental variable. The instrument is statistically significant with a large coefficient estimate at 1% level in probit models and effective F statistic for the instrument is above the Staiger and Stock (1997) rule of thumb critical value 10 except for 15-19-years-old girls sample. A widespread practice among researchers to test weak identification in linear IV models with non-i.i.d errors is to present first stage robust F statistic and compare it to Staiger and Stock (1997), or Stock and Yogo (2005) critical values. However, there is no theoretical or empirical justification for this exercise as Staiger and Stock (1997), and Stock and Yogo (2005) critical values are determined for the case of conditionally homoscedastic and serially uncorrelated errors[60] (Baum, Schaffer, and Stillman, 2007; Olea and Pflueger, 2013). Olea and Pflueger (2013), besides providing an alternative non-i.i.d robust pretest for weak instruments, also adjusts the critical values. Their rule of thumb critical value for 2SLS is equal to 23.1 for the null hypothesis that the Nagar (1959) bias of the 2SLS estimator is larger than 10% of the "worst-case" bias with a test size of 5%. To clarify this point, the "worst-case" bias corresponds

[60] Baum, Schaffer and Stillman (2007) point out that the use of Wald F statistic (robust F statistic) based on Kleibergen-Paap rk statistic as a robust alternative to Cragg-Donald F statistic has not been justified in the context of weak identification of IV model, and thus is not a formal test for weak identification. Yet, they argue that Kleibergen-Paap rk Wald F statistic is superior to Cragg-Donald F statistic in the presence of heteroskedasticity, autocorrelation or clustering. They additionally suggest using Kleibergen-Paap rk Wald F statistic as a test for weak identification with Staiger and Stock (1997) critical value of 10 in models with non-i.i.d errors. Olea and Pflueger (2013), by showing that both non-robust and robust F statistics may yield high values even when instruments are weak, provide grounds for the warnings that Baum, Schaffer and Stillman (2007) express regarding the usage of Kleibergen-Paap rk Wald F statistic as a pretest for weak identification.

to the bias in the 2SLS estimator when instruments are completely weak and an effective F statistic of order 23.1 or higher leads to rejection of the null at 5% significance level and eventually one can conclude that the instruments are strong in the sense that the bias of the 2SLS estimator is no more than 10% of the "worst-case" benchmark. With respect to Olea and Pflueger's (2013) weak instrument pretest methodology, the instrument proves to be strong for the sample of children between ages 6 and 14, and for sample of boys aged 15 to 19 as the corresponding effective F statistics are larger than 23.1. For sample of girls aged 15 to 19, the instrument may be weak and the bias resulting from weak instrumental variable identification may push 2SLS estimates towards OLS estimates (Bound et al., 1995). We offer two solutions to this problem. Even though the best remedy is to find additional instruments that satisfy strong identification, it is extremely difficult to apply this method in our case. Albeit, we present Anderson-Rubin (1949) test for the coefficient estimate of the endogenous regressor in IV 2SLS estimation which is a weak instrument robust test for the null hypothesis that the coefficient estimate of the endogenous regressor equals to zero in the structural equation. Plus, we test with parametric and semiparametric IV models by excluding region level covariates that capture the labor market characteristics including share of men aged 20 to 64 with high school and above high school degree, unemployment rates for males of ages 15-64, share of men aged 15-64 working in agriculture and the share of men aged 15-64 working in private sector. Omitting labor market determinants for samples of 15-19-years-old girls results in effective F statistic for the instrument of order 11.89 which in turn leads to a strong instrument by Staiger and Stock (1997) critical value, or by Olea and Pflueger (2013) critical value if one is willing to tolerate a bias for the 2SLS estimator that is up to approximately 30% of the worst-case bias. We try to assess whether the endogenous variable is sensitive to the exclusion of the labor market characteristics from both the structural and the reduced form equations. By the help of this test, we will also be able to see whether the instrument affects the outcome through labor market characteristics in addition to its influence through remittances. Lastly, experimenting with different IV estimators may help lessen the bias that is brought about by 2SLS estimator[61]. One such estimator is LIML estimator which is known to be more robust to weak instruments—has lower bias and lower mean squared error—compared to 2SLS. Fuller's modified LIML is an alternative k-class estimator which has better finite-sample performance under weak instruments compared to 2SLS but neither LIML nor Fuller's LIML are robust to deviations

[61] Different estimators have differing power in detecting treatment effects under weak instruments. 2SLS is one of the least robust estimators for weak instruments. It has been shown that critical values for weak-instruments test are larger for 2SLS compared to alternative estimators (Baum, Schaffer and Stillman, 2007; Olea and Pflueger, 2013).

from i.i.d disturbances (Baum, Schaffer and Stillman, 2007). One last alternative considered is the "continuously updated" GMM estimator (CUE) of Hansen, Heaton and Yaron (1996) which is a GMM generalization of LIML estimator to the case of non-i.i.d errors. CUE uses numerical optimization methods to derive coefficient estimates and we couldn't achieve convergence for the models with suspected weak identification problem. Therefore, we couldn't make use of the LIML, Fuller's LIML or CUE estimators. One last point about pretests which try to assess the strength of the instrument is that both robust F statistic and effective F statistic could be applied to test weak instruments in the context of linear IV models only. The first stage of a linear IV model consists of a linear probability model but the underlying relation between the endogenous variable and the included and excluded exogenous regressors may be better explained by a nonlinear fit to the data, and this may produce different power schemes for the same instrument in linear and nonlinear IV models. Actually, the relevance of an instrument is established based on results from two tests. Firstly, for an exactly identified model, the coefficient estimate of the instrument in the regression of the endogenous variable on exogenous variables (included and excluded ones) should prove to be statistically different than zero. This is the test for underidentification of the model. A sufficiently small p-value for the instrument leads to rejection of the null that the model is underidentified. This step helps to establish a significant nonzero correlation between the endogenous regressor and the excluded instrument. However, having an adequately identified model is not sufficient to obtain correct inference. That being said, having an instrument that is uncorrelated with the endogenous regressor results in the IV estimator to have a bias that is equivalent to the bias of the OLS estimator and a larger mean squared error. Plus, the IV estimator becomes inconsistent (Hahn and Hausman, 2002; Baum, Schaffer and Stillman, 2007). After establishing a significant nonzero correlation between the endogenous variable and the instrument, the second step involves determining the size of the correlation. A coefficient estimate for the instrument that is close to zero but statistically significant in the regression of the endogenous variable on the exogenous regressors implies a weak correlation between the endogenous variable and the instrument. In that case, similar serious bias problems arise with IV GMM and 2SLS models (Bound et al., 1995; Baum, Schaffer and Stillman, 2007). Cragg-Donald F statistic and its robust counterparts are used to test for weak identification of linear IV models. As pretests for weak identification do not exist for nonlinear models such as IV bivariate probit and (IV) SNP, by analogy to the linear case, we check the p-value of the instrument in the regression of the endogenous variable on exogenous regressors and the size of the coefficient estimate of the instrument. A low p-value and a large coefficient estimate are considered to indicate a strong instrument in our nonlinear regressions. Most of our nonlinear specifications do reveal a strong identification based on the above definition of a weak instrument.

Table 1-6 and Table 1-7 present the estimates of the determinants of remittance receipt for samples of adult males and females (aged 20-64), respectively. The dependent variable is a dummy indicating whether an adult lives in a recipient household. For males, a systematic difference with respect to educational attainment on the likelihood of living in a recipient household seems to occur only for prime-age group. For this age group, educational attainment is negatively associated with the likelihood of being in a recipient household (the omitted base category is being illiterate). For males over 25 years of age being the household head decreases the chances of receiving remittances for their households. This finding may be due to the relationship between the sender and receiver of remittances. Most of the remittance receiving households with a missing spouse constitute of female headed households which implies a negative association between the presence of a male household head and remittance receipt. For 20-24-years-old males being married is negatively associated with living in a recipient household. 85% of 20-24-years-old males still live with their parents. 18% of 20-24-years-old males are married with only 1% of married 20-24-years-olds report receiving remittances. Since a high fraction of recipient males aged 20 to 24 live with their parents, a better comparison group for them is non-recipient males of same age who live with their parents. Therefore, we experiment with both the unrestricted and restricted sample of 20 to 24 years old males to assess the impact of remittances on their labor supply behaviors. The highest level of educational attainment of household members do not seem to influence the likelihood of receiving remittances. A better infrastructure of the household seems to increase the probability of receiving remittances. Living in rural areas is positively associated with remittance receipt only for 20-24-years-old males. The number of children aged 0 to 5 and of school aged females have a negative influence on the likelihood of being in a recipient household. Number of adult males and females have remarkably similar impacts on receiving remittances as in the first stage regressions for samples of children. Households in historically underdeveloped regions appear to be more likely to receive remittances. For 20-24-years-old males, the income inequality in a region is positively associated with the probability of receiving remittances. Share of men aged 25-64 in a region with above high school education has a negative impact on a household's chances of receiving remittances. A high fraction of men with above high school education may reflect the economic prosperity of the region and abundance of employment opportunities for young individuals which may result in a reduced demand for foreign earnings. Unemployment rate is again a significant determinant of remittance receipt. Share of men in agriculture and share of men in private sector have positive impacts on remittance receipt for 50-64-years-old and 20-24-years-old males, respectively. The global recession in 2008 seems to manifest its impact on households' remitting behavior beginning in year 2008 and lasting till the end of 2010. The evidence presented in Table 1-6 suggests that concerns of weak identification are not likely to be a major issue. The instrument is always statistically significant at 1% level with a large coefficient estimate and the effective F statistic is over 10; only slightly less than the threshold level for elderly males. With respect to Olea and Pflueger (2013) critical values, the instrument is strong in the sense that the maximal bias of the 2SLS estimator is no more than 5% of the worst-case benchmark for young males, and is no more than 20% of the worst-case benchmark for prime-age males. For elderly males, Olea and Pflueger (2013) methodology provides evidence for weak identification of the model.

The first stage results for adult females are presented in Table 1-7. On contrary to first stage regression results of adult males, highest level of educational attainment in the household matters especially for women over 50 years of age. The impacts of older women's own educational attainment and the highest level of educational attainment of household members counteract on the likelihood of living in a recipient household. Prime-age women are less likely to live in a recipient household if they have more than high school education. This is reasonable as earnings potential is higher for highly educated individuals and an increase in household income would be accompanied with a decrease in the need for foreign earnings to support the household. The opposite holds for 20-24-years-old women. The results suggest that households with female heads are more likely to be recipients. Married females are more likely to reside in recipient households except for women of ages 20-24. Almost 55% of recipient women of ages 20-24 live with their parents which makes non-recipient women of same age who live with their parents a better comparison group for them. As is with the male sample of ages 20-24, we test the impact of remittances for women of ages 20-24 both with and without restricting them to live with their parents. Number of preschool children and of school age females negatively affects the remittance receipts for prime-age women. The estimates of coefficients on number of adult males and females are on par with the corresponding results from the regressions of adult males. The signs of the region level covariates that capture the economic conditions of regions in the past seem to support the hypothesis of Ayhan et al. (2000); although most of the estimates are not statistically significant. The unemployment rate and year dummies have similar impacts as in the preceding cases on the likelihood of living in a recipient household with a more pronounced statistical significance for the year 2009. The effective F statistic and p-value of the Wald test for the historical migration rate provides evidence on the strength of the instrument and confidence in the identification strategy when weak-instruments tests are based on Staiger and Stock (1997) critical values. With respect to Olea and Pflueger (2013) critical values, the effective F statistic is large enough to reject the null of 2SLS bias being no more than approximately 20% of the worst-case benchmark for prime-age and elderly women. For younger females, the instrument does not appear to be strong in the sense that the null of 2SLS estimator bias exceeding 30% of the worst-case benchmark cannot be rejected.

Table 1-8 presents estimates of determinants of remittances for households. The dependent variable is a binary capturing the remittance receipt status of a household. Households with medium level of educational attainment for the member with highest schooling outcome are more likely to receive remittances compared to households with all members illiterate. This result is in line with migration incurring significant costs and households with very low educational levels (low earnings potential) being unable to afford to migrate and receive remittances in return. Age of the household head only slightly matters for households with older heads. A better infrastructure of the household is associated with higher chance of receiving remittances. Number of preschool children has a negative influence on the probability of receiving remittances. Number of male adults and female adults have impacts that are comparable to the preceding cases. Unemployment rate of a region and year fixed effects for 2008, 2009, and 2010 are statistically significant determinants of remittance receipt. The instrument is statistically significant at 1% level with a large coefficient estimate and with an effective F statistic of order 16 which is considered to be large enough for strong identification. For all samples, the first stage results of the instrumental variable suggest that households which are located in historically high emigrating regions are more likely to receive remittances.

1.4.2 Main Results

1.4.2.1 Child human capital investment decisions

In this section, we try to assess whether receiving remittances alters household spending on child human capital accumulation. We use school attendance and literacy of children as a means to measure investments on child human capital by their families. The focus is on children between ages 6-14 and 15-19. We run separate regressions by gender for each age group.

Delays in starting school and grade repetition cannot be captured by the current school attendance of children. This is more of a concern especially if there is a systematic difference in school starting age between recipient and non-recipient children since grade repetition of a student in compulsory schooling level is an extraordinary situation in Turkey and can only be agreed upon if the parents of the student give written consent for it. Possibility of grade repetition thus cannot compromise the results for children at compulsory schooling level. However, if a particular group of children (recipient or non-recipient) systematically delays starting schooling, then it is possible to observe the other group catching up at older ages. The greater attendance at older ages for the late starters would then be artificially attributed to the remittance receipt status of the household. Nevertheless, our data does not provide evidence for a significant difference in school attendance rates at age 5 for recipient and non-recipient children. Grade years accumulated by a child at a given age is an alternative measure of child human capital investment which is implemented in the context of migration impacts on schooling by Hanson and Woodruff (2003), and McKenzie and Rapoport (2011). Our data provides last finished schooling of children instead of accumulated years of schooling. Therefore, we couldn't test the robustness of our measure of child human capital investment with this alternative measure.

Each presented table of results consists of three panels. Panel A includes coefficient estimates for the impact of remittances on various outcomes from four models: parametric non-IV probit, parametric IV 2SLS and IV bivariate probit, and semi-parametric IV SNP. For remittance coefficient estimate, both Huber-White heteroskedasticity robust standard errors and cluster robust standard errors are presented. We provide both types of standard errors to highlight the importance of accounting for the grouped nature of the observations. Though, statistical inference will always be based on the cluster robust standard errors. Huber-White heteroskedasticity robust standard errors are presented in parenthesis and cluster robust standard errors are presented in brackets. Panel B includes p-values for the Wald test of remittances from various methods which correct for the downward bias in standard errors of remittances resulting mainly due to the finite number of clusters. Corrections are applied for all non-IV and IV models other than SNP. For all parametric models, asymptotic refinement of the Wald test is basically achieved through recalculating p-values based on larger than standard normal critical values which come from t distribution with varying degrees of freedom. Besides calculating p-values based on t distributions, we make use of wild restricted efficient residual bootstrap of Davidson and MacKinnon (2010); restricted score cluster bootstrap of Kline and Santos (2012); and pairs cluster bootstrap-t and calculate p-values accordingly. The latter two methods are implemented for IV bivariate probit and the former method is applied for IV 2SLS. For non-IV probit model asymptotic refinement is provided through restricted score cluster bootstrap in addition to t distributed Wald test statistic. Unfortunately, for (IV) SNP model estimating cluster robust standard errors is extremely time consuming, and hence neither estimated standard errors account for intra-cluster error correlation nor asymptotic refinement of the Wald test through recalculating p-values based on t distribution, score cluster bootstrap, or pairs cluster bootstrap-t methods could be achieved. Panel C mainly constitutes of test statistics regarding: the endogeneity of the remittance variable; the strength of the instrument; the statistical significance of the estimated remittance impact in IV 2SLS models for which weak identification is suspected to be a threat; and the bivariate normality of errors in bivariate probit models. These tests include in order: Wald test of ρ=0 in IV bivariate probit, endogeneity test of suspected regressor in IV 2SLS via Wooldridge's (1995) robust score test which accounts for the intra-cluster correlation of errors[62]; p-value for the Wald test of the excluded instrument in the regression for the determinants of remittances in IV bivariate probit and SNP, effective F statistic for the instrument in the first stage of IV 2SLS; p-value of Anderson-Rubin test in IV 2SLS; and p-value of score test of normality for bivariate probit models[63].

Based on findings of Maddala (1983) whenever the latent regression errors u_{Tig} and u_{Yig} in system of equations (2) are independent, then one can consistently estimate parameter vectors of the model by separately estimating two univariate probit models, one for T_{jtg} and one for Y_{ijtg}. However, when latent regression errors are not independent, then separate estimation of two univariate probit models results in inconsistent parameter estimates in the equation for Y_{ijtg}. The endogeneity of remittances implies a nonzero correlation between latent regression errors. Knapp and Seaks (1998) has shown that a likelihood ratio test of ρ=0 (a zero correlation between latent regression errors) has the power to unravel the endogeneity of a dummy variable in a bivariate probit model. Stata reports Wald test of ρ=0 in place of likelihood ratio test when the bivariate probit model is estimated with robust standard errors. This is the test we present as an empirical evidence for the endogeneity of remittances and is simply comparing the sum of log likelihoods from univariate probit regressions of T_{jtg} and Y_{ijtg} with the log likelihood from IV bivariate probit model. Under the null of exogeneity of remittances the sum of log likelihoods from univariate probit regressions is equal to log likelihood from bivariate probit model.

Anderson-Rubin test is a weak instrument robust test of the null hypothesis that the coefficient of the endogenous variable is equal to zero in the structural equation. This test is also robust to violations of i.i.d errors assumption through heteroskedasticity, serial

[62] Wooldridge's (1995) score test is implemented in Stata by "*estat endogenous*" postestimation command of Stata's built-in ivregress command.

[63] Score test of normality for bivariate probit used in this study is a modified version of Murphy's score test by Chiburis (2010) and is implemented in Stata by "*scoregof*" command.

autocorrelation, or clustering[64]. Anderson-Rubin test is not efficient whenever the instrument is strong. In other words, with strong instruments Wald t test is more powerful compared to Anderson-Rubin test. Thus, Anderson-Rubin test is only presented for 2SLS models where the efficient F statistic is not large enough to reject the null of 2SLS bias exceeding one tenth of the worst-case bias.

Wild restricted efficient residual and restricted score cluster bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. Pairs cluster bootstrap-t p-values are only reported for IV bivariate probit models and only for models where the Wald test of remittances based on clustered standard errors reject at statistical significance levels 10% and lower. This is due to the necessity of excessive amount of time for Stata to estimate bivariate probit regression equations 1,999 times. On the other hand, WRE and score bootstraps need to run the corresponding models (IV 2SLS and IV bivariate probit) only once; thus, need considerably less time compared to pairs cluster bootstrap-t and are presented for IV 2SLS and IV bivariate probit even though the p-value of Wald test of remittances is larger than 0.10.

1.4.2.1.1 Child school attendance and illiteracy

Tables 1-9, 1-10, and 1-11 present results of the impact of remittances on school attendance of children aged 6 to 14, on illiteracy among children between 6 and 14 years of age, and on school attendance for older children of ages 15-19, respectively.

We first begin by examining the differences in school attendance of 6- to 14-year-old males and females owing to the remittance receipt status of their households. The dependent variable is a dummy taking value 1 if the child attends school and 0 otherwise. Besides the main regressor of interest (remittances) all models also include year fixed effects in addition to individual, household and region level covariates: a dummy for the observation being the oldest child in the household, last finished schooling of the parent, dummies for marital status and age of the household head, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gross enrollment ratio of children aged 6 to 10 in 1985 by region, and gini of household income by region. It is important to point out that for any outcome that we

[64] Anderson-Rubin test for IV 2SLS model is implemented in Stata by "*weakiv*" command.

investigate the impact of remittances on, household income/wealth is never included in the set of controls, although it proves to be an important determinant of various outcomes in our context (see, e.g., Acosta [2006], Acosta [2011]). Household income/wealth is a function of migration because of the monetary and in-kind funds that can be provided to the household thanks to migration, and the changes in the allocation of labor supply in the household that is induced by migration. Controlling for household income/wealth, thus, shuts down several key channels through which migration affects outcomes, especially the mediator that we focus on in this study—remittances. Omitting household income/wealth would result only in an increase in error variation as our identification strategy does not require to condition on household income/wealth[65].

OLS (probit) results suggest that receiving remittances is associated with higher school attendance of both males and females aged 6 to 14, although the impact is imprecisely estimated. After accounting for the endogeneity of remittances, for both genders the direction of the impact on school attendance remains; however, IV 2SLS and IV bivariate probit estimates of remittance impact are statistically insignificant at conventional levels for the sample of boys. Murphy's score test of normality rejects the null hypothesis that latent regression errors have bivariate gaussian distribution in IV bivariate probit specifications for girls' and boys' school attendance[66]. Thus, to test the robustness of IV bivariate probit results columns (4) and (8) present IV SNP estimates which point to positive and marginally significant effect of remittances on school attendance of both girls and boys with the size of the impact being larger for girls. Unlike estimates from IV 2SLS and IV bivariate probit specifications for boys, both estimators yield statistically significant effect of remittances for girls. IV 2SLS estimate in column (6) proves to be statistically significant at 5% level under any alternative method that corrects for the downward bias in estimated standard errors due to few clusters. The IV bivariate probit estimate of remittances in column (7) remains statistically significant when pairs cluster bootstrap-t procedure is implemented. Restricted score cluster bootstrap, though, suggests that there is not enough evidence in the data to reject a zero impact of remittances on school attendance of girls. Using t distribution for the Wald t statistic produces p-values that are more in line with the pairs cluster bootstrap-t p-value compared to restricted

[65] Since our instrument is at regional level, the possibility of regional income inequality that is persistent both in the past and in the present would threaten its validity, hence the identification strategy in this study. We include regional income gini to address this particular concern.

[66] Murphy's score test almost always reject the hypothesis that errors have bivariate standard normal distribution in IV bivariate probit specifications, except for the regression of labor supply choice of 20-24-year-old females who currently live with their parents.

score cluster bootstrap p-values. Mostly in our analysis, restricted score cluster bootstrap—regardless of the weights used in bootstrapping the scores and the assumed shape of the distribution of the Wald statistic—produces significantly larger p-values compared to those from t distributed Wald statistic and pairs cluster bootstrap-t technique. In columns (3), (5), and (6) cluster robust standard errors are estimated to be smaller than heteroskedasticity robust standard errors despite the relation is expected to hold in the other direction as cluster robust standard errors are both heteroskedastic and cluster robust (see, e.g., Cameron and Miller [2015]), which may emphasize the extent of the downward bias in cluster robust standard errors when there are few clusters[67].

The instrument proves to be a strong predictor of the likelihood of receiving remittances: effective F statistic is larger than Staiger and Stock (1997) rule of thumb critical value and also is large enough to reject the null that the Nagar bias of the IV 2SLS estimator is more than 10% of the "worst-case" bias; the instrument is statistically significant at 1% level in the regression for determinants of remittances in IV bivariate probit and IV SNP specifications. The corresponding rows in Table A1 provides evidence for the exogeneity of the instrument to the households' school attendance decisions for their children aged 6 to 14. Woolridge's score test suggests that remittances should be treated as endogenous in IV 2SLS, however the Wald tests of $\rho=0$ yield large p-values which implies that there is no evidence against the hypothesis that receiving remittances is exogenous in IV bivariate probit specifications of young children's school attendance. Maddala (1983) notes that maximum-likelihood estimates from univariate probit regressions are consistent and asymptotically efficient when $\rho=0$, but are biased and inconsistent when $\rho\neq0$. On the other hand, IV bivariate probit estimates are consistent regardless of the correlation between latent regression errors. Albeit the evidence in the data, trading off some noise in the estimates with relief from concerns of potential inconsistencies is, thus a good practice.

The coefficient estimates in Table 1-9, as noted before, are not directly comparable to each other. Therefore, in Table 1-25 we present treatment effects of remittances—LATE and ATE (AME)—, which we can compare with each other, on school attendance and other outcomes. The first two rows in Table 1-25 summarize the treatment effect of remittances on school attendance of children aged 6 to 14. Probit results show a small and insignificant impact of remittances on school attendance of both genders. When we instrument the remittance receipt

[67] Theoretically when errors are negatively correlated in clusters or intra-group correlation has a modest impact, cluster robust standard errors could be smaller than Huber-White heteroskedastic-robust standard errors, although in practice it is more likely to have larger cluster robust standard errors (Cameron and Miller, 2015).

status of the household, the effects become larger, although for boys the effects are insignificant in IV 2SLS and IV bivariate probit specifications. Evidence from IV SNP estimation suggest that, on average, boys from recipient households are 2.4 percentage points more likely to attend school with the effect being statistically significant at 1% level. For girls, the same estimation method shows that being in a recipient household increases the likelihood of attending school by 3.2 percentage points. For girls, the average marginal effect of remittances is significantly larger from IV bivariate probit estimates compared to the marginal effect from IV SNP estimates. The difference in the marginal effects may be an indicator of the extent of the bias in IV bivariate probit estimates when bivariate standard normal distributed errors assumption is violated. Still, the positive impact from IV SNP remains in IV bivariate probit. The IV 2SLS estimate for girls is positive, large, and statistically significant. Though, it is impossible to interpret the LATE as it is outside the unit interval. Simply, difference between two probabilities can never exceed 1 in absolute value. The mechanical interpretation of the effect, though, is that being in a recipient household increases the chances of attending school by 250 percentage points for girls from households whose remittance receipt status complies with the instrument. There is always a large difference between LATE of IV 2SLS and ATE of IV bivariate probit, and confidence intervals of IV 2SLS estimates are large—thus leading to point estimates mostly outside of the unit interval—, which as noted by Chiburis et. al. (2011) may be a flaw of IV 2SLS estimator due to having a low share of remittance receiving households in the sample.

The change in the size of the effects between non-IV and IV methods reveal that children aged 6 to 14 from recipient households have unobserved characteristics which make them seem less likely to attend school compared to their non-recipient counterparts. In other words, in the absence of migration and remittance receipt, children who are currently in remittance receiving households would have lower school attendance rates compared to children from observationally similar non-recipient households. Experiencing negative income shocks on the side of remittance-recipient households would be consistent with the results.

To sum up, OLS (probit) results suggest a zero impact of remittances on school attendance of children between ages 6 and 14. After addressing self-selection of remittance-recipient households, robust evidence shows that children indeed benefit from remittances by increasing their chances to attend school by around 2-3 percentage points. This may be consistent with remittances alleviating liquidity constraints and help parents attain the desired level of schooling for their children, even in compulsory schooling level where resource constraints are assumed to be not that much of a concern in sending children to school due to free of charge provision of the education services.

Table 1-10 presents the estimates of the impact of being in a recipient household on illiteracy of children between ages 6 and 14. The dependent variable is a dummy taking value 1 if the child is illiterate and 0 otherwise. The same set of controls as in Table 1-9 is used in estimating child illiteracy regressions. Probit estimates of remittance coefficient are negative, small and insignificant. For boys, the claim still holds when we instrument for receiving remittances, except for a very large, negative and significant effect that IV 2SLS yields. Once we test with different rejection methods though, the impact becomes insignificant. For girls, IV bivariate probit result suggests a negative and statistically significant effect of remittances. However, when we account for the downward bias in the cluster robust standard errors with restricted score cluster bootstraps and pairs cluster bootstrap-t, the impact becomes statistically insignificant. The IV 2SLS point estimate is, as in for boys, very large, negative, statistically significant and the effect is robust under alternative rejection methods. Treatment effects calculated using the IV estimates in Table 1-10 suggest that boys from recipient households, on average, are 2 to 5 percentage points less likely to be illiterate; and girls from recipient households, on average, are 6 to 7 percentage points less likely to be illiterate compared to their non-recipient counterparts.

Next, we examine the differences in school attendance of children aged 15-19 years old due to remittance-receipt status of their households. For this age group schooling is not compulsory and further, outside work opportunities are available. Remittances may reduce the household’s need to rely on children’s labor via substituting labor income of children. Thus, children may free up some time from work that they can allocate to schooling activities and eventually increase their human capital. In addition, remittances may be used to finance schooling expenses of children that wouldn’t be possible to defray in the absence of migration of a household member and the remittances sent in return. Columns 1-4 in Table 1-11 refers to schooling outcomes of boys, and the rest of the columns refer to the schooling outcomes of girls. The dependent variable is a dummy taking value 1 if the child attends school and 0 otherwise. Besides remittances and educational reform dummy, models in columns 1-8 also include year fixed effects in addition to individual, household and region level covariates: a dummy for the observation being the oldest child in the household, last finished schooling of the parent, dummies for marital status and age of the household head, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region.

First thing to notice is that regardless of the gender, in any model educational system reform is estimated to have a positive and highly significant impact on school attendance of 15-19-year-old children. This implies a positive spillover effect of the reform on high school attendance and is in line with the findings of Aydemir and Kırdar (2017). For males, probit and IV bivariate probit results show a zero impact of remittances on school attendance, although the point estimates have opposite signs. IV 2SLS and IV SNP model estimates of remittances also have opposite signs but they are both statistically significant[68]. IV 2SLS estimate is also robust to alternative calculation methods of p-value of the Wald test. The discrepancy in the direction of the impact between IV 2SLS and IV SNP highlights the importance of checking for the validity of the model assumptions and using alternative estimators if possible. As a result, robust evidence suggests that boys aged 15-19 from recipient households are more likely to attend school compared to observationally similar boys from non-recipient households. This result is consistent with remittances reducing household budget constraints and helping finance schooling expenses of children.

For females we first consider the results in columns 5 to 8. Probit estimate of remittances in column (5) is positive and insignificant. However, all IV methods in the remaining three columns present a negative and significant impact of remittances on school attendance. The change in the sign of the impact between non-IV and IV methods reveal that migration/remittances decision and school attendance of girls are positively correlated, i.e. initially, girls who are currently in remittance receiving households are more likely to attend school compared to their non-receiving counterparts. The migration of a caring parent—in regard to schooling activities of the girl—is consistent with the result. The absence of the caring parent due to migration reduces the parental input into the girl’s schooling acquisition and it seems that the negative impacts of migration (e.g., the absence of a parent/role model, the

[68] The SNP estimate is marginally significant with a p-value of 0.096.

disruption of the family structure, the additional workload on children both in and outside of the house to replace the migrant's labor) outweighs the positive impacts of remittances for 15-19-year-old females.

The significance of IV bivariate probit estimate of the remittance impact in column (7) is only robust under hypothesis testing based on t distribution with varying degrees of freedom. It is important to state that the significant difference in p-values that pairs cluster bootstrap-t and restricted score cluster bootstraps yield may be due to being unable to successfully run all bootstrap replications for pairs cluster bootstrap-t procedure. Kline and Santos (2012), in that case, suggest that one should approach pairs cluster bootstrap-t results with caution. Another concern with estimation results from columns 5 to 8 is having a weak instrument. The effective F statistic is only 3.62 and the instrument in the regression of determinants of remittances in IV bivariate probit specification is only marginally significant with a p-value of 0.099. The p-value of the Wald test of the instrument in SNP model is even worse: 0.407. We implement two approaches to attack the weak instrument problem. Firstly, we run Anderson-Rubin test of the coefficient estimate of remittances being equal to zero in the structural equation. Anderson-Rubin test is a weak instrument robust test that allows for violations of i.i.d errors assumption in IV 2SLS models, and basically runs the reduced form estimation of outcome on all excluded and included instruments. If the excluded instruments are jointly significant in the reduced form, then the test concludes that there is enough evidence to reject the hypothesis of zero impact of remittances in the structural equation. p-value of Anderson-Rubin test in column (6) is small enough to reject zero impact of remittances in favor of the negative impact that IV 2SLS estimator produced. Secondly, the abundance of regional level controls may create collinearity in the first stage and reduce the predictive power of the instrument. Hence, we exclude regional labor market characteristics[69], and consequently the effective F statistic of the instrument increases to a level that is large enough to reject IV 2SLS bias of order 30% or higher of the "worst-case" bias; the p-value of the Wald test of the instrument drops to 0.004 and 0.06 in IV bivariate probit and IV SNP specifications, respectively. The results in columns 9 to 12 are qualitatively similar to those in columns 5 to 8; even the significance levels of the estimates agree except for the IV 2SLS model in which the impact of remittances is estimated to be statistically insignificant and the size of the impact is attenuated towards zero. Since the size of

[69] The excluded regional labor market characteristics are: share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region.

the coefficient on remittances stays almost the same in regressions with and without regional labor market characteristics as controls, one is inclined to argue that excluding labor market controls would not threaten the exogeneity of the instrument. However, Table A1 presents evidence against this hypothesis. Being in a historically high migration region is shown to have a direct impact on school attendance of girls from non-receiving households aged 15-19—distinct than its impact through migration and remittances, most likely capturing impacts of omitted labor market characteristics on school attendance—when regional labor market characteristics are omitted; on the contrary, there is no evidence against a zero impact of the instrument on school attendance of the same group when regional labor market controls are included. The estimates in columns 9 to 12 may be inconsistent as the instrument may be invalid. Only the negative estimate of the impact in column (6) seems to be robust to alternative methods of rejection and weak instruments. The average marginal effect of remittances from SNP estimates in Table 1-11 is statistically significant and on average, boys aged 15-19 from recipient households are 8 percentage points more likely to attend school compared to their non-receiving counterparts; and the corresponding effect for girls from IV bivariate probit and SNP estimates are negative and sizable 15 to 29 percentage points.

Summing up, boys of ages 6 to 19 increase their school attendance; girls between ages 6 and 14 increase both their school attendance and their literacy rates; and girls aged 15 to 19 decrease their school attendance in response to receiving remittances. Where do our findings stand in the literature? The increase in boys' (aged 6 to 19) school attendance is in line with the finding of remittances reducing dropout hazard rates of 6 to 24 years old males in El Salvador (Cox-Edwards and Ureta, 2003). Lopez Cordova's (2005) finding of a significant negative impact of remittances on illiteracy of children between ages 6 and 14 is comparable to our result for girls aged 6 to 14. The extent of the decrease in girls' (aged 16 to 18) likelihood to attend school in response to the migration of a household member found by McKenzie and Rapoport (2011) is in the range of the extent of the decrease in the likelihood of school attendance for girls aged 15 to 19 in our study. McKenzie and Rapoport (2011) found a significant decrease in school attendance of boys aged 12 to 18 which is in stark contrast with our finding of a positive impact of remittances on school attendance of 6-19-year-old males.

1.4.2.1.2 Child labor

In this section, we focus on the labor force participation decisions of children aged 15 to 19. We mainly investigate the extent of the change in take up rates of overall market work, wage work, unpaid family work, and self-employment for children from remittance-recipient households.

Table 1-12 presents the point estimates of the impact of remittances on boys' labor supply choices. The dependent variables are dummies capturing labor force participation decisions of boys: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of his own either by employing someone for a wage or employing unpaid family workers, and being employed in any of the aforementioned market work, respectively. The same set of controls in the corresponding columns for boys in Table 1-11 is used to estimate boys' labor supply behavior regressions.

In any model, being affected by the education system reform is estimated to decrease both boys' and girls' likelihood to do any kind of work. This finding suggests that children who were forced to stay three more years in lower secondary school are more likely to substitute market work with schooling activities even later in their lives. The education reform implemented in 1997 seems to benefit the children in accumulating human capital even after 8 years of compulsory schooling period has ended.

IV bivariate probit estimates of the remittance impact in Table 1-12 are statistically insignificant regardless of the outcome variable. IV 2SLS and IV SNP estimates disagree in the size of the effect in regressions of overall labor market participation and wage work; and disagree in the sign of the impact in regressions of unpaid family work and self-employment. Since SNP estimator is more robust to non-normal errors and performs better when treatment probabilities are low compared to IV 2SLS estimator, we prefer to rely on IV SNP estimates. Boys from remittance receiving households are less likely to work as unpaid family workers and more likely to be self-employed compared to their counterparts from non-recipient households, and the effects of remittances are highly significant. There is no impact of remittances on overall labor force participation and wage work. The change in the sign of the impact between probit and IV SNP estimates suggest that the decision to send remittances and self-employment of boys are negatively correlated, i.e. boys from remittance-recipient households are initially less likely to be self-employed compared to their counterparts. For a prospective migrant to decide on migrating and sending remittances, it may be necessary to have household members that can replace the migrant's labor, and in this case, it seems that remittances are more likely to be received by households where participation rates for 15- to 19-year-old males are low. Having said that, Table A1 provides evidence against the exogeneity of the instrument in the model for a 15- to 19-year-old male's likelihood to be self-employed and the p-value of the coefficient on the instrument in the determination of remittances from IV SNP model is 0.064 which may result in the identification to be weak. Thus, the only reliable result is the reduction in a boy's likelihood to do unpaid family work in response to receiving remittances. The average treatment effect of remittances from IV SNP estimates suggest that boys from recipient households are 7 percentage points less likely to perform unpaid family work. This result reveals that for boys the income effect of remittances outweighs other impacts of migration. For boys of ages 15 to 19 it seems that some time reallocation takes place favoring schooling activities over unpaid family work. Taking together the results from school attendance and child labor determination, the robust evidence suggests that boys of ages 6 to 19 from remittance-recipient households are better off with respect to human capital accumulation compared to their counterparts.

Tables 1-13 and 1-14 present the estimates of being in a remittance-recipient household on labor supply decisions of girls aged 15 to 19. The estimates in Table 1-13 suffer from weak instrument problem; thus, as in school attendance decisions of girls aged 15 to 19, we run separate regressions of labor supply choices for girls omitting regional labor market characteristics in Table 1-14. From both regressions—with and without labor market characteristics—, one robust result follows: receiving remittances reduces a girl's likelihood to be self-employed. In Table 1-13, Anderson-Rubin test rejects a zero impact of remittances on wage work and self-employment; nevertheless, the IV 2SLS estimates are statistically insignificant but point to a negative impact on these outcomes and the direction of the effect agrees with the statistically significantly estimated impact from IV SNP method for wage work[70]. However, the instrument appears to be redundant in the IV SNP specification of wage work as the p-value of the instrument in the regression for determinants of remittances is close to 1. In Table 1-14, the predictive power of the instrument for remittances is large enough—the effective F statistic exceeds Staiger and Stock (1997) rule of thumb critical value—and the impact of remittances on wage work and self-employment is estimated to be negative and highly significant from both IV 2SLS and IV SNP methods[71]. The Anderson-Rubin test also rejects a zero impact of remittances on wage work and self-employment in favor of the negative estimate at a 5% statistical significance level. We may not be able to satisfy exogeneity assumption of

[70] The IV SNP estimate of remittance impact is not available for self-employment. Since there is no variation in self-employment for girls in recipient households and a very small variation for girls in non-recipient households, nonlinear models (e.g., probit, IV bivariate probit, and IV SNP) have difficulties in estimation process.

[71] Though in Table 1-14, the instrument in IV SNP method never proves to be a significant determinant of remittances; the p-value of the instrument is always larger than 0.10.

the instrument in overall market work and unpaid family work specifications in regressions with and without labor market controls, plus in wage work specification where we do not control for the regional labor market characteristics. This leaves us with self-employment specifications where we might achieve strong and valid identification. There is also evidence in Table 1-14 for a decrease in a girl's overall labor market participation from IV bivariate probit specification; however, once we check with the IV SNP estimator to account for the non-normality of errors, the impact vanishes, plus the IV bivariate probit estimate of remittance impact becomes statistically insignificant when we implement restricted score cluster bootstrap techniques. The average treatment effect of remittances on self-employment is estimated to be very close to zero; whereas, the local average treatment effect suggests a lower probability of self-employment for girls from recipient households of order 21 percentage points. The large difference in treatment effects on self-employment may stem from the differences in sub-groups for which the effects are estimated. As for the boys in the same age group, the income effect of remittances dominates other impacts of migration for girls.

Girls of ages 15 to 19 from recipient households reduce their school attendance, and the robust evidence argues that the time that is freed up from school is not allocated to market work. An important question arises: what are those girls from recipient households doing instead of continuing their education or participating in the labor market? A reasonable answer would be to help with household chores, especially if the labor of the migrant is substituted by the household member who were responsible of taking care of the household chores. Another answer would be to engage in activities other than schooling and market work. There is no information in the data on a household member's engagement in household/subsistence work or time spent on other kinds of activities such as taking computer courses, sewing courses, etc. Therefore, the question will be left unanswered.

Yang (2008) shows that a positive exchange rate shock results in a decline in hours worked in unpaid family work for boys between ages 10 and 17. Acosta (2011) finds a lower probability for wage work and non-wage work for girls of ages 10-18 from recipient households. Alcaraz, Chiquiar and Salcedo (2012) contribute to the literature by finding of a negative effect of remittances on child labor. Our results of a decline in unpaid family work for boys aged 15-19 from recipient households; and a decline in non-wage work for girls aged 15-19 from recipient households are in line with these preceding results in the literature.

1.4.2.2 Adult labor supply responses

In this section, we examine the labor supply responses of left behind household members aged 20 to 64. The income effect of remittances may increase the reservation wage of household members, and consequently result in a decrease in market work participation. On the other hand, members of the household may need to substitute for the absent migrant's labor/income which translates into an increase in the labor supply or a shift between different employment types (wage to non-wage, non-wage to non-wage, or non-wage to wage work). Observing a decrease in the labor supply of left behind adults implies a pure income effect; however, an increase in the labor supply may stem from replacing migrant's labor/income or from productive use of remittance income in household enterprises. We examine the impact of remittances on adult labor supply responses discriminating by gender and age of the respondent.

1.4.2.2.1 Labor supply responses of adult males

1.4.2.2.1.1 20-24-years-old males

As is described in section 1.4.1, a high share of 20-24-years-old males currently live with their parents, so restricting the estimation sample to males aged 20-24 who live with their parents is an alternative way to investigate the impacts of remittances on a young male's labor supply response with the data in hand. We run regressions for labor supply responses of young males first without restricting the sample and then by restricting the sample. Tables 1-15 and 1-17 present the estimates of being in a recipient household on labor supply responses of young males without and with the sample restriction, respectively.

In both model specifications—with and without sample restriction—, the dependent variables are the same as in child labor regressions. Besides the main regressor of interest, all models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the individual being the household head, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. In Table 1-17, we exclude from model specification the dummy for the observation being the household head, since all 20-24-years-old males live with their parents, this covariate becomes redundant.

The common impact of remittances for the samples of 20-24-years-old males is a significant decline in overall market participation. In Table 1-15 this decline appears to be the result of a simultaneous decline in wage work and self-employment; whereas in Table 1-17 it is a consequence of a simultaneous decline in unpaid family work and self-employment. However, unpaid family work results from both samples may prove to be inconsistent as there is enough evidence in the data against the exogeneity of the instrument. In both samples, the instrument has a very strong predictive power on the likelihood of receiving remittances; although, its power is somewhat reduced in the first stage for sample of males who live with their parents. The exogeneity of remittances in the structural equation in both samples cannot be rejected for any employment type either by Wooldridge's score test or Wald test of $\rho=0$, except for unpaid family work regression for the whole sample of young males which, as noted before, might have already violated assumptions of IV estimation by making use of an invalid instrument. The probit estimates and the estimates from IV estimators have the same sign in both samples; nonetheless, only the negative point estimate on overall labor force participation from probit model is statistically significant and robust to rejection method based on using t distribution for Wald statistic. IV 2SLS estimator is unable to ravel significant point estimates for any employment type in either of the samples. IV bivariate probit estimates find significant negative impacts of remittances on overall labor market participation and self-employment for the whole sample of young males. These point estimates from IV bivariate probit become marginally significant at 10% and 11% levels, respectively once we implement pairs cluster bootstrap-t technique to correct for the downward bias in the estimated standard errors. Pairs cluster bootstrap-t results should be taken with a grain of salt as Wald statistic could not be estimated in some bootstrap replications. IV SNP estimator, which is the preferred econometric estimation method, finds negative, and significant impacts of remittances on overall labor force participation, wage work and self-employment for the sample of whole young males. The remittance effect does not change much when we exclude young males living on their own from regression analysis: the negative impact on wage work for the whole sample of young males remains but it becomes statistically insignificant; the negative insignificant impact on unpaid family work becomes statistically significant, however, as noted before, results from unpaid family work regressions may be inconsistent. Average treatment effect of remittances for the whole sample of young males suggests that being in a recipient household is estimated to significantly lower: overall market work of young males by 10 to 45 percentage points, wage work by 23 to 29 percentage points, unpaid family work by 4 to 14 percentage points, and self-employment by 3 to 6 percentage points depending on the estimator. The corresponding ATEs from point estimates in the restricted sample suggest that receiving remittances reduces: overall labor market participation by 10 to 24 percentage points, wage work by 16 percentage points, unpaid family work by 4 to 15 percentage points, and self-employment by 2 to 5 percentage points. The evidence is suggestive of the dominance of income effect on 20-24-years-old males' labor supply responses. Observing a decline in labor market participation brings about the possibility of a time reallocation by 20-24-years-old males favoring schooling activities over market work. Remittances by reducing liquidity constraints may help finance schooling of 20-24-years-old males and allow an increase in human capital of young males which may translate into higher earnings for them in the future. However, robust evidence suggests that young males from recipient households are less likely to attend school compared to non-recipient counterparts[72]. This result may imply that remittances are sent for reasons other than financing of a 20-24-years-old male's schooling expenses.

The change in the size of the effects between probit and IV methods imply that young males from recipient households have unobserved characteristics which make them look more likely to engage in market work compared to non-receiving counterparts. Financial losses of the household such as job loss of a member would have required other members to contribute to the household budget in the absence of remittances. With the migration of a member and the non-labor income provided to the family by means of remittances, the household's need for other members to supply their labor might have vanished.

1.4.2.2.1.2 25-49-years-old males

Table 1-19 presents the estimates of the impact of remittances on labor supply decisions of prime-age men. The same set of covariates as in Table 1-15 are used in model specifications for prime-age men.

The results suggest that there is a decline in wage work of prime-age men in response to receiving remittances, and an increase in unpaid family work and self-employment. The decrease in wage work more than offsets the increase in non-wage work which results in a

[72] The results on a 20-24-years-old male's likelihood to attend school are available from authors upon request.

significant decline in labor force participation. The evidence reveals that to some extent, time substitution takes place favoring non-wage work over wage work, but income effect dominates substitution effect in overall. The results imply that for some remittance receiving families, left behind male members need to substitute the absent migrant's labor, and for the rest the additional income through remittances is large enough to incentivize prime-age men to quit the labor market.

The point estimate from probit model in column (1) proves to be negative, statistically significant under any alternative rejection method, and contradicts with the point estimate from IV bivariate probit in column (3) regarding the sign of the impact. IV bivariate probit estimate on overall labor force participation proves also to be statistically significant under rejection methods based on t distribution and pairs-cluster bootstrap-t. It would be misleading to rely on IV bivariate probit estimate of remittances in this particular case, as the robust estimator to non-normality of errors find a negative, and statistically significant point estimate at 1% level.

For wage work, all the estimators point to a significant, negative effect of remittances. All the alternative rejection methods for probit, IV 2SLS and IV bivariate probit agree on the statistical significance of the point estimates. For unpaid family work, the point estimates from available estimators are all positive, and statistically significant in IV SNP specifications and in IV 2SLS under different rejection methods. For self-employment, robust estimators to endogeneity of remittances find positive and statistically significant estimates, and the significance levels of the estimates remain under different rejection methods for IV 2SLS and IV bivariate probit.

The instrument is strong enough to reject IV 2SLS bias of order 20% or higher of worst-case bias. Still, we present Anderson-Rubin test results which support the statistical inference on remittances in wage and non-wage work regressions. Table A1 shows that there is no evidence in the data to reject the exogeneity of the instrument to labor supply decisions of prime-age men.

The results in Table 1-25 on average treatment effect of remittances suggest that receiving remittances is estimated to significantly lower the chances of overall market work of prime-age men by 10 to 23 percentage points depending on the estimator. The decline in wage work ranges between 9 to 50 percentage points, the increase in unpaid family work is between 2 to 10 percentage points, and lastly the increase in chances of being self-employed varies from 4 to 40 percentage points. ATEs from IV SNP estimates are more conservative compared to ATEs from IV bivariate probit which are two to eight times larger. The change in the size of the effects between non-IV and IV results in Table 1-25 reveal that remittance decision is positively correlated with both wage-work and overall labor market participation of prime-age men. In addition, there is a negative correlation between remittance decision and non-wage work. That is, in the absence of remittances, prime-age men from remittance receiving households are more likely to work for wage and participate in the labor market; and are less likely to be self-employed and work as unpaid family worker compared to non-receiving counterparts. For a prospective migrant having household members that could replace his labor in household enterprises is an important factor in deciding to migrate, and the evidence justifies this hypothesis by finding an initially lower participation rate for prime-age men in recipient households.

1.4.2.2.1.3 50-64-years-old males

Table 1-21 presents the estimates for the impact of being in a recipient household on labor supply of 50-64-years-old males. We use the same set of independent variables as in labor supply response specifications for prime-age men. First thing to notice is the low predictable power of the instrument on the likelihood of receiving remittances in IV 2SLS models. The effective F statistic of the instrument in the first stage is 8.87 which is less than Staiger and Stock (1997) critical value. On the other hand, the instrument is statistically significant at 1% level in the regression for determinants of remittances with nonlinear models. Thus, the instrument may prove to be strong in nonlinear models.

The IV bivariate probit estimates suggest that elder males shift from unpaid family work to self-employment in response to receiving remittances, and the increase in self-employment more than offsets the decrease in unpaid family work resulting in an overall increase in labor market participation. IV SNP estimate supports the claim of a significant increase in overall market work; however, for unpaid family work and self-employment the point estimates from IV SNP become insignificant even though the direction of the impacts agrees with the ones from IV bivariate probit. Estimates from IV bivariate probit regressions of labor market participation, wage work and self-employment appear to be robust to reject a zero-impact null hypothesis with testing based on t critical values. Restricted score cluster bootstrap runs into some problems in calculating p-values and hence, p-values are not available. Pairs cluster bootstrap-t could not estimate Wald statistics in each bootstrap replication; nonetheless, suggests that receiving remittances significantly increases the likelihood of elder males to engage in self-employment.

IV 2SLS estimator yields a negative and significant estimate of the impact on wage work and this point estimate is robust to weak instrument identification—with a test size of

10%. However, WRE bootstraps reveal that there is a sizable downward bias in standard errors due to having few heterogenous clusters. Therefore, statistical inference with IV 2SLS estimator may be unreliable. On the other hand, Wooldridge's score test presents evidence against the exogeneity of remittances, so probit results might be misleading, too. Alternative IV methods suggest a zero impact of remittances on an elder man's likelihood to work for a wage.

The last of the problems with regressions of 50-64-years-old males' labor supply decisions is about the validity of the instrument. There is enough evidence to support the claim that the instrument has a direct impact on self-employment and overall labor market participation of elder males. As a consequence, for 50-64-years-old males we might have been unsuccessful in fully addressing the endogeneity of remittances.

In a nutshell, probit results find a significant decline in an elder male's likelihood to work for a wage and engage in self-employment, resulting in an overall significant decline in labor force participation. On the other hand, the robust evidence from IV bivariate probit reveals a significant increase in labor force participation of elder males which decomposes into a simultaneous significant increase in self-employment and a decline in unpaid family work. When we account for the observed differences between recipients and non-recipients, OLS results are consistent with the observational evidence. Once we account for the endogeneity of remittances, IV bivariate probit results suggest an increase in labor supply of elder males—mainly resulting from the increase in self-employment—which is consistent with remittances being sent to invest in the origin country in household enterprises. ATE of remittances from probit estimates suggest that being in a recipient household significantly reduces likelihood of overall labor force participation by 17 percentage points, wage work by 5 percentage points, and self-employment by 11 percentage points. ATE of remittances from IV bivariate probit reveals a significant increase in self-employment of order 38 percentage points, a significant increase in labor market participation of order 34 percentage points, and a significant but mere 1 percentage point decrease in unpaid family work. ATE of remittances from IV SNP estimate on elder men's overall market work is a significant increase by 25 percentage points. The consistency in ATEs of remittances on labor supply choices from probit and IV bivariate probit models does not remain in IV SNP model, e.g. in probit specification the decrease in overall labor force participation is due to a simultaneous decrease in wage work and self-employment; in IV bivariate probit specification the increase in overall market work is brought about by an increase in self-employment; however, in IV SNP specification the increase in overall market labor force participation cannot be explained by a change in participation in any employment type. This discrepancy might also be a result of the estimation issues inherent with regressions of elder males' labor supply responses.

To sum up, we find a significant negative impact of remittances on 20-49-years-old men's overall market work. For 20-24-years-old males this negative impact is brought about by a decrease in wage work and self-employment; for prime-age men the decline appears to be the result of a decrease in wage work. Prime-age men also increase to an extent unpaid family work and self-employment in response to receiving remittances but compared to the decline in the likelihood of working for a wage, the increase in non-wage work is not sizable. The impact of remittances on a 20-24-years-old male's labor supply behaviors does not change much once we run separate regressions for young males who currently live with their parents. The observational evidence on the dominance of income effect for adult males appears to have a causal interpretation for 20-49-years-olds. The robust evidence on a 50-64-years-old male's labor supply response reveals a dominant substitution effect. Rodriguez and Tiongson (2001) find that migration reduces labor force participation of 15-64-years-old males in Philippines, which is due to the income effect of remittances dominating the substitution effect of migration. Our results show dominance of income effect on labor supply decisions of adult males aged 20- to 49-years-old in Turkish context. As explained before, there also exists a sizable substitution effect for prime-age men. Amuedo-Dorantes and Pozo (2006) show that Mexican males substitute formal wage work with informal wage work in response to a household member's migration to defray migration costs and replace the absent migrant's labor income. In our case, the motivations for prime-age and elder males to increase non-wage work seem to be a result of productive use of the remittances in household enterprises or of the need to replace absent migrant's labor, but not his income.

1.4.2.2.2 Labor supply responses of adult females

Migration of a household member and the remittances sent may provide opportunities for left behind females to enter the labor market and earn their own income. Females through reallocating time from household chores to productive market work may increase their bargaining power and strengthen their position in the household. In allocating household resources females may play a more important role compared to the counterfactual situation in the absence of remittances. On the other hand, remittances might have been large enough to increase females' reservation wages and have not been channeled into productive uses which simply translate into a decline in females' market labor force participation. In this section, we investigate the change in the labor supply of females due to receiving remittances. We try to quantify the impact discriminating by age of the respondent.

1.4.2.2.2.1 20-24-years-old females

As is with the sample for 20-24-years-old males, a high share (49%) of 20-24-years-old females still live with their parents which makes testing the impacts of remittances on labor supply choices of young females discriminating by their residence a reasonable alternative. The dependent variables are dummies capturing labor force participation decisions of females: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of her own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work, respectively. Besides remittances all models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the individual being the household head, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. We discard a dummy variable which indicates whether the observation is the household head from regression specifications for 20-24-years-old females who currently live with their parents.

Table 1-16 presents the estimates of the impact of remittances on labor supply choices of whole sample of 20-24-years-old females. Probit results, which do not account for the endogeneity of remittances, cannot reject zero impact hypothesis for any employment type but are suggestive of an increase in non-wage work and a decrease in wage work and overall labor market participation. Probit results are in line with the observational evidence. IV results, on the contrary, find a significant, negative impact on young women's overall labor force participation which appears to be a result of a simultaneous and significant decline in both wage work and self-employment. Remittances appear to affect labor supply choices of 20-24-years-old males and females in the same way: income effect of remittances increase to an extent the prices of labor for left behind 20-24-years-old males and females that is large enough to make them decrease their labor force participation rates. Do young females continue schooling instead of taking part in the labor force? IV models of school attendance could not detect a statistically significant change in a young female's likelihood to attend school owing to receiving remittances[73]. It is not possible to further investigate what young females do with the additional time they saved from market work, though.

IV bivariate probit estimates are negative and statistically significant for wage work and self-employment, and insignificant for overall labor force participation. IV SNP point estimates improve upon IV bivariate probit estimates by finding a statistically significant (at 1% level) negative impact of remittances on overall market work. The necessity to check the robustness of IV bivariate probit estimates are justified by very low p-values that score tests of normality yield. IV bivariate probit estimates on wage work and self-employment are robust to rejecting based on t distribution, plus point estimates on self-employment remain statistically significant under pairs cluster bootstrap-t correction. Interestingly, restricted score cluster bootstraps for IV bivariate probit estimate on wage work yield lower p-values than the controversial rejection method based on standard normal distribution. It looks like something goes wrong with the implementation of the method since the unrestricted score cluster bootstraps give p-values that are larger than the standard normal distribution based p-value for the Wald test. IV 2SLS estimates find a negative, significant effect on wage work and a significant, positive effect on unpaid family work. These estimates are robust to testing based on t critical values. Anderson-Rubin test also rejects a null impact of remittances on wage work in favor of the negative effect which provides more confidence in the negative and significant effect that IV bivariate probit and IV SNP reveal. However, WRE bootstraps suggest that IV 2SLS estimates have too narrow confidence intervals and, therefore statistical inference from IV 2SLS may be misleading. The instrument is strong with a first stage effective F statistic of order 10.18; the p-values of the Wald tests for the instrument from nonlinear IV regressions on the likelihood of receiving remittances are very close to zero. The ATEs of remittances from IV SNP estimates suggest that 20-24-years-old girls from recipient households are 13 percentage points less likely to work

[73] The results are available from authors upon request.

for a wage, merely 1 percentage point less likely to engage in self-employment, and as a result 17 percentage points less likely to participate in labor force.

Once we restrict the estimation sample to 20-24-years-old females who still live with their parents, almost all of the point estimates in Table 1-18 become insignificant, except for a barely significant positive impact that IV SNP method yields on overall labor market participation; and a significant positive impact that IV 2SLS method finds on the likelihood to be self-employed. The statistical inference from IV 2SLS proves to be robust to rejecting based on WRE bootstrap and t distribution. However, the instrument is weak with a first stage effective F statistic of order 5.87, and Anderson-Rubin test is unable to detect a weak identification robust significant impact of remittances on self-employment. Thus, the IV 2SLS estimate may be no better than the OLS estimate with respect to the size of the bias. The score test could not reject bivariate normality of errors, so for any employment type the IV bivariate probit model appears to be correctly specified which renders IV bivariate probit estimation strategy more efficient than IV SNP (De Luca, 2008). IV bivariate probit is unable to detect the positive, significant impact of remittances on overall labor market participation that IV SNP finds. Nevertheless, IV SNP estimate would most likely become statistically insignificant if we could have controlled for the intra-group error correlation. As a conclusion, the evidence suggest that remittances do not affect labor supply behaviors of 20-24-years-old girls who live with their parents. The income and substitution effects seem to cancel each other. Cox-Edwards and Rodriguez-Oreggia (2009) find a similar null effect of remittances on labor supply choices of 12-65-years-old males and females.

As a side note, a technical issue prevents estimation of remittance impact on self-employment by probit and IV bivariate probit: all young females from recipient households choose not to engage in self-employment which implies that remittances perfectly predict the outcome (not being self-employed). In such cases, Stata chooses to drop the independent variable and estimates the remaining model with nonlinear estimators such as logit, probit, and bivariate probit.

1.4.2.2.2.2 25-49-years-old females

Table 1-20 presents the estimates of the change in a 25-49-years-old female's labor supply due to being in a recipient household. The same set of independent variables as in Table 1-16 are used in model specifications for prime-age women's labor supply behaviors.

To begin with, the instrument has a large first stage effective F statistic, plus the point estimates of the instrument are statistically significant at 1% level from regressions of prime-age females' likelihood to be in a recipient household in nonlinear IV models. The distributional assumption on the latent regression errors of IV bivariate probit model seems not to be satisfied which necessitates testing the results from IV bivariate probit estimator with the robust alternative method, IV SNP. Sample sizes for prime-age males' and females' labor supply response regressions are very large compared to those from young and elderly males' and females' regressions, still the IV 2SLS point estimates exceed 1 in absolute value which may empirically justify Chiburis et. al. (2011) finding of a poorly performing IV 2SLS estimator when treatment probabilities are low.

Probit estimates find a null impact of remittances on labor supply behavior of prime-age women. Once we account for the unobserved heterogeneity that affects both the likelihood to receive remittances and labor supply choices, the coefficient of interest is estimated to significantly lower the probability of working for a wage and overall market work, and increase the likelihood to engage in self-employment. The robust evidence suggests that to some extent prime-age women shift from wage work to self-employment in response to receiving remittances; however, a significant decline in overall labor force participation for women reveals that the income effect of remittances dominates the substitution effect.

IV point estimates of the impact of remittances on wage work and overall labor market participation appear to be undisputed. For wage work, all IV estimates are negative and highly significant; furthermore, statistical inference from IV 2SLS and IV bivariate probit regressions is robust to any rejection method. However, there is evidence in the data that we were unable to control for all the channels—distinct than remittances—through which migration networks could affect likelihood of working for a wage[74]. This finding may cloud the reliability of the results on wage work. For overall market work, IV bivariate probit estimate of the impact is negative and statistically significant at 1% level. Rejection methods based on t distribution, restricted score cluster bootstrap and pairs cluster bootstrap-t all reject a null impact of remittances at conventional significance levels. Pairs cluster bootstrap-t was unable to estimate the Wald statistic in 5 bootstrap replications; however, once we further analyze the results, we became aware of a pattern: for labor supply regressions of males and females regardless of the age, and for household well-being regressions, pairs cluster bootstrap-t cannot estimate the Wald statistics in the exact same 5 bootstrap replications which implies that the problem stems from the seed that is used to randomly draw clusters in Stata's bootstrap command. If the

[74] When we include fixed effects for broad geographical regions, the instrument exogeneity appears to be satisfied; however, it leads to less precise estimation of remittance impact in main regressions.

resultant 5 bootstrap samples have no or very limited variation in treatment and this causes missing t statistics, then it is unexpected to have valid inference by making use of the remaining bootstrap distribution (Cameron and Miller, 2015). On the other hand, if the missing t statistics occur by chance, then its impact on having valid inference would be minor. Since nonparametric pairs resampling method takes too much time to estimate the bootstrap distribution of Wald statistic, we couldn't test our claim by making use of another seed. IV SNP estimate of the impact confirms the finding of a negative and significant effect of remittances by IV bivariate probit. For unpaid family work, IV 2SLS and IV bivariate probit suggest a positive impact of remittances but the results are only robust to rejecting based on t critical values. Besides, IV SNP estimator cannot detect a significant impact of remittances on unpaid family work. Only IV SNP estimator finds a significant positive impact of remittances on prime-age women's likelihood to engage in self-employment. ATE of remittances from IV SNP estimates suggest that prime-age women decrease their overall market work by 6 percentage points and wage work by 8 percentage points, and increase self-employment by 16 percentage points—although the coefficient of remittances on self-employment is marginally significant—in response to receiving remittances. The robust evidence on labor supply choices of prime-age women is consistent with the observational evidence and with findings of a significant decline in labor force participation for women by Acosta (2006), Lokshin and Glinskaya (2009), Amuedo-Dorantes and Pozo (2006), and Rodriguez and Tiongson (2001).

1.4.2.2.2.3 50-64-years-old females

Table 1-22 presents the estimates of the impact of being in a recipient household on labor supply decisions of 50-64-years-old females. If the family uses remittances to make investments on behalf of the absent migrant—through setting up a new household enterprise or maintaining an existing one—, then it is expected to observe an increase in the labor supply of left behind family members and it would be easier for those members who would have lower participation rates in the absence of remittances to increase their labor supply: elderly males and elderly females. The robust evidence on labor supply behavior of 50- to 64-years-old males reveal a significant increase in overall market labor force participation which appears to be resulting from a significant increase in self-employment. Females of ages 50- to 64-years-old decrease wage work in response to receiving remittances and do not differ from non-recipient counterparts with respect to their labor supply in non-wage work and overall market work. This finding may imply that elderly males in the family are more likely to replace the absent migrant's duties in managing the household enterprise.

OLS results on 50-64-years-old females' labor supply responses suggest a null impact of remittances, except for a statistically significant negative effect on unpaid family work; IV results suggest a statistically significant negative impact of remittances on wage work only, and the point estimates from IV 2SLS and IV bivariate probit are robust to alternative rejection methods. Moreover, tests of exogeneity show that remittances should be treated as endogenous both in IV 2SLS and IV bivariate probit models of wage work which reveals that the point estimate from probit model is biased. The change in the sign of the impact on wage work for 50-64-years-old females shows that females from recipient households are initially more likely to work for a wage in the absence of remittances maybe due to the household receiving a negative income shock which is not observed by the econometrician. The ATE of remittances on wage work for elderly females is a statistically significant decline of order 3 to 4 percentage points depending on the estimator.

To sum up, females regardless of their age appear to decrease wage work in response to receiving remittances. The decline in wage work is not large enough to significantly affect overall market work for 50-64-years-old females, but for women of ages 20- to 49-years-old the decline in wage work causes a significant decline in market labor force participation rates. Recipient women of ages 20- to 24-years-old are also less likely to engage in self-employment. Prime-age women substitute wage labor with self-employment to an extent, but the increase in self-employment is not large enough to neutralize the decline in wage work.

1.4.2.3 Remittances and the welfare of households

For a household, one of the main motivations behind the decision to send a member abroad is to accumulate foreign exchange earnings, and by means of this funding improve living conditions of the left behind family members. Remittances by providing investment opportunities may diversify income sources of the household. Even if remittances are not channeled into productive uses, it may be used to achieve higher consumption levels for the household. Yang (2011) states that neither of the uses—consumption or investment—can be argued to be better as a priori: on one hand, it may be the best choice for the household to spend remittances on consumption, especially if they suffer from very low income levels; on the other hand, for households with sufficient income levels it may be optimal to use remittances on household investments, particularly if the productive investments would not have been achieved without the extra income derived from remittances due to the resource constraints. In times of monetary crisis, households may also benefit from the insurance role of remittances and survive through difficult times more easily (Cox, Eser, and Jimenez, 1998; Gubert, 2002).

Lastly, remittances sent may not be large enough to improve welfare of the household to an extent that consumption levels of recipient households exceed subsistence consumption levels.

There are various channels through which remittances may affect household welfare, and in this section, we try to quantify the impact of remittances on household well-being. To measure the welfare status of a household, we make use of poverty indicators that determine the relative position of the household in household income or expenditure distributions. It is extremely difficult to use absolute poverty measures in our analysis because the amount of the expenditure on durable goods and non-food items in a month by a household must be subtracted from a household's monthly expenditure and the basket of durable goods are unknown to us. Moreover, food poverty lines are no more calculated by TÜİK since 2011. Therefore, we prefer to rely on relative measures of poverty. The calculation of relative poverty measures based on household income do not change much from country to country and thus, organizations like OECD, EUROSTAT and TÜİK prefer to use this measure[75]. TÜİK uses different proportions of the median of the per adult equivalent yearly disposable household income distribution as cutoffs for poverty line (i.e., 40%, 50%, 60% and 70%) and suggests implementing 50% and 60% cutoffs in studies on poverty. In international comparisons of household well-being, another widely used measure is per adult equivalent daily expenditure levels of 1$, 2.15$ and 4.30$. TÜİK adds another expenditure based measure to the set of poverty indicators in which the cutoff for a household to be considered poor is set to 50% of the median of the per adult equivalent monthly household expenditure. We use all three kinds of poverty measures.

Table 1-23 presents the estimates of the impact of being a recipient household on welfare status of the household measured by the relative position of the household in the income distribution. The dependent variables are dummies capturing household well-being taking values 1 if the household is located below 40%, 50%, 60% or 70% of the median of the per adult equivalent yearly household disposable income distribution, and taking values 0 otherwise. Since households come from different years, to have comparable income and expenditure values we inflate the prices to December 2011 using TÜİK's consumer price index. To have comparable household sizes, we make use of a modified version of OECD's equivalence scale which counts the first adult in the household as 1, and the remaining members who are older than 14 years of age as 0.5 and younger than 14 years of age as 0.3. Besides the main regressor of interest, all models also include year fixed effects in addition to household

[75] Tüketim Harcamaları, Yoksulluk ve Gelir Dağılımı – Sorularla Resmi İstatistikler Dizisi – 6, Türkiye İstatistik Kurumu, Yayın No: 3186.

and region level covariates: a dummy for having a married household head, dummies for the age of the household head, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region.

The instrument has a strong predicable power on a household's likelihood to receive remittances, and there is no evidence in the data against the exogeneity of the instrument; thus, we achieve strong and valid identification for poverty regressions where measures of household well-being are based on the relative position of the household in the per adult equivalent yearly household disposable income distribution. The impact of remittances seems to vary depending on the estimator and the cutoff used for the poverty line. When poverty line is set to 40% of the median of the per adult equivalent yearly household disposable income distribution, IV 2SLS estimate points to a negative and statistically significant impact of remittances on poverty. The point estimate is robust under alternative rejection methods. Anderson-Rubin test rejects a null impact of remittances in favor of the negative effect. IV bivariate probit shows a negative and statistically significant impact of remittances but the point estimate is not robust under restricted score cluster bootstrap and pairs cluster bootstrap-t. IV SNP finds a negative but insignificant impact of remittances. The coefficient of remittances from probit regression is negative and statistically insignificant; however, both tests of exogeneity reveal that remittances are endogenous and should be treated accordingly. The evidence on poverty with 40% cutoff is mixed with respect to the statistical significance of the estimate of the impact, though the direction of the impact is in favor of recipient households.

When poverty line is set to 50%, the only statistically significant estimate comes from probit regression; although the point estimate may prove to be biased. The statistical significance of the IV 2SLS estimate is not robust to the downward bias in the standard errors due to having few clusters. All estimates show a negative impact of remittances on poverty with 50% cutoff but IV results are not statistically significant. Therefore, it is safe to argue that once we control for the endogeneity of remittances, recipient and non-recipient households are not significantly different than each other with respect to their position relative to the 50% cutoff in the income distribution.

When the cutoff is increased to 60%, robust evidence suggests a statistically significant decline in poverty rates for recipient households. The preferred estimator (IV SNP) finds a statistically significant negative impact of remittances on poverty; whereas other IV methods cannot detect a significant impact of remittances. Probit result is consistent with the finding of IV SNP model. Therefore, if we define a poor household as one which is located below 60% of the median of the per adult equivalent yearly household disposable income distribution, the evidence reveals that being a recipient household decreases the probability of living under poverty line.

When the poverty line cutoff is further increased to 70%, IV methods cannot find a significant difference between recipient and non-recipient households in the likelihood of being poor. Probit estimate shows a negative and significant impact of remittances on poverty.

ATEs of remittances from probit estimates suggest that regardless of the cutoff used to define poverty, being a recipient household reduces the chances to be poor by 2 to 4 percentage points. Once we account for unobserved heterogeneity that affects both selection into treatment and outcome variables, ATE from IV bivariate probit estimates suggests that recipient households are 10 percentage points less likely to be positioned below 40% of the median of the per adult equivalent yearly household disposable income distribution; ATE from IV SNP estimate reveals that recipient households are 5 percentage points less likely to be poor based on the poverty measure with 60% poverty line cutoff. As a conclusion, robust evidence shows an improvement in the welfare of households in response to receiving remittances particularly for poverty indicators with 40% and 60% cutoffs.

Table 1-24 presents the estimates of the impact of being a recipient household on poverty, this time to quantify household welfare, expenditure patterns of households are used as basis. The first dependent variable comes from TÜİK’s definition of relative poverty based on monthly household expenditures: households with per adult equivalent monthly household expenditure levels below 50% of the median of corresponding expenditure distribution, are considered to be poor. The latter two dependent variables are widely used definitions of relative poverty in international comparisons based on expenditure patterns of households: daily per adult equivalent expenditure levels of 1$, 2.15$, and 4.30$. There is very limited variation in dependent variable for 1$ expenditure level which makes it impossible to estimate the impact of remittances. Therefore, we are left with 2.15$ and 4.30$ expenditure levels as outcome variables.

The results are in line with the preceding findings: recipient households are better off compared to non-recipient counterparts. In each specification, exogeneity of remittances is rejected; hence, probit estimates of coefficient on remittances may be biased. IV 2SLS and IV bivariate probit results in columns (2) and (3) reveal conflicting impacts of remittances on poverty. IV 2SLS estimate suggests a statistically significant improvement in household welfare due to receiving remittances; however, IV bivariate probit finds a statistically significant worsening impact of remittances. Both estimates are robust to rejecting based on t critical values. Pairs cluster bootstrap-t produces some missing Wald statistics in estimation process; thus, may not provide valid inference. Actually, the p-value from pairs cluster bootstrap-t is smaller than the conventional p-value of the Wald statistic which may justify our concern with the validity of the inference. IV SNP result suggests a negative impact of remittances but the point estimate is not statistically significant. In conclusion, the robust evidence reveals a null impact of remittances on a household's likelihood to be placed below 50% of the median of the per adult equivalent monthly household expenditure distribution. ATEs of remittances from IV bivariate probit estimates and IV SNP estimates are in agreement: members of recipient households are around 7 percentage points more likely to be consuming less than 50% of the median of the per adult equivalent monthly household expenditure distribution. ATE of remittances from probit, on the contrary, suggests that recipient households are 3 percentage points less likely to be placed below the 50% cutoff.

For daily per adult equivalent expenditure levels, IV 2SLS estimates show statistically significant and negative impacts of remittances. The point estimates are robust to rejection with alternative methods. In addition, Anderson-Rubin test rejects null impact of remittances on both 2.15$ and 4.30$ expenditure levels. IV bivariate probit finds a statistically significant and negative impact of remittances on living under 2.15$ per day, but the estimate is not robust under restricted score cluster bootstraps. Pairs cluster bootstrap-t has some missing Wald statistics which cast some clouds on the validity of the inference. IV SNP point estimates suggest that remittances do not affect the likelihood of living under 2.15$ or 4.30$ per day. Probit estimates find a significant negative impact on the likelihood of living under 4.30$ per day. To conclude, robust evidence from IV 2SLS models suggest that members of recipient households are significantly less likely to live under 2.15$ per day (by 16 percentage points) and under 4.30$ per day. The corresponding ATEs of remittances from IV bivariate probit estimates suggest a significant 0.3 percent decline in the likelihood to live under 2.15$ per day, and an insignificant 0.6 percent decline in the probability to live under 4.30$ per day. ATEs of remittances from IV SNP are insignificant on both expenditure levels and are similar in magnitude to ATEs from IV bivariate probit estimates. ATEs from probit estimates suggest a zero impact on the likelihood to live under 2.15$ per day and a significant mere 1 percent decline in the likelihood to live under 4.30$ per day.

The empirical analysis with both income and expenditure based poverty measures shows an important result: recipient households are doing better compared to non-recipients even after accounting for observable and unobservable differences between households. This result is consistent with the observational evidence and with the Adams and Page's (2003) finding of a decline in the share of people living under 1$ per day in response to an increase in received remittances.

1.5 Conclusion

This study explores the impact of remittances on child human capital investment decisions, child labor, adult labor supply choices and household well-being. We acknowledge that our identification strategy cannot isolate the impacts of remittances from other impacts of accompanying migration, and hence the results are best interpreted as joint effect of remittances and other impacts of migration. We pay much attention to deal with the endogeneity of remittances in the analysis. We present IV estimates with a widely used instrument in the literature of the impact of migration on various household outcomes, which is historical migration rates by region. To achieve a valid instrument, regression analysis includes numerous region level covariates through which the instrument is suspected to affect outcome variables. We do not control for broad geographical regions in our regressions. Including indicators for geographical regions does not significantly affect the size of the coefficient estimates; though it leads to less precise estimation of remittance impact as expected. An indirect test of the exogeneity of the instrument is presented in an Appendix, and the results provide more confidence in our identification strategy. We make use of a semiparametric IV estimator in addition to IV 2SLS and IV bivariate probit estimators which are the most frequently used estimators recently in the literature that estimates bivariate binary choice models. The semiparametric IV estimator improves upon others by allowing less restrictive assumptions on error distributions. The evidence shows that being unable to satisfy model assumptions have important consequences on the estimates. Lastly, to account for possible intra-group error correlation, we use cluster robust variance matrix estimator, and to correct for the downward bias in standard errors due to having few clusters, we implement alternative rejection methods that are suggested in the literature. The results reveal that there is a great chance of rejecting a true null hypothesis when one relies on asymptotic cluster robust standard errors in the presence of heterogenous and few clusters. At least, one should make small sample modifications and use t(G-1) critical values for the Wald test as noted by Cameron and Miller (2015).

We find evidence of an increase in school retention rates of 6- to 14-years-old children regardless of their gender, and an increase in 6- to 14-years-old girls' literacy rates in response to being in a recipient household. Remittances have counteracting impacts on school attendance of 15- to 19-years-old boys and girls. While boys aged 15 to 19 benefit from higher schooling, girls of same age are less likely to be present at school. Remittances by alleviating liquidity constraints is expected to have a positive impact on school attainment of children; thus, the negative impact of remittances on school attendance of 15- to 19-years-old girls is most likely a result of dominance of disruptive effects of migration over income effect of remittances. The impact of remittances on child labor choices favor income effect hypothesis. Boys aged 15 to 19 in recipient households are less likely to work as unpaid family worker, and girls aged 15 to 19 in recipient households are less likely to be self-employed. There appears to be a time substitution favoring schooling over market work for recipient boys of ages 15-19-years-old, while girls of ages 15-19-years-old are losing out on both schooling and experience in labor market due to receiving remittances. To sum up, remittances improve schooling outcomes of boys of ages 6- to 19-years-old and girls of ages 6- to 14-years-old, and lead to lower school retention for girls aged 15-19-years-old and to lower child labor.

We also examine the impacts of remittances on left behind males' and females' labor supply decisions. Income effect of remittances by increasing reservation wages may cause a decline in adult labor supply. On the other hand, the substitution effect of migration and productive uses of remittances in household enterprises may require adults to increase their labor supply. Our results are in line with these predictions. For 20- to 24-years-old males, remittances reduce labor force participation which appears to be a result of a simultaneous decline in both wage work and self-employment. For 25- to 49-years-old males (prime-age), remittances cause to some extent a shift from wage work to unpaid family work which may stem from the need to replace the absent migrant's labor; however, the income effect is substantially stronger than the substitution effect that eventually causes a significant decline in market labor force participation. For 50-64-years-old males, receiving remittances is associated with an increase in overall labor market participation. Males of ages 50- to 64-years-old replace unpaid family work with self-employment maybe to substitute for the absent migrant's responsibilities in management of household enterprise or due to productive uses of remittances in setting up new household enterprises. Summing up, we find evidence on the dominance of income effect of remittances for 20- to 49-years-old males, and on the dominance of substitution effect for 50- to 64-years-old males.

Labor supply responses of females aged 20 to 49 years-old resemble their male counterparts' responses. Females of ages 20- to 24-years-old decrease their labor force participation in response to receiving remittances, and the decline is due to a significant and simultaneous decline in wage work and self-employment. Prime-age women in recipient households decrease wage work and increase self-employment, and the overall impact is a significant decline in labor force participation. For 50- to 64-years-old females, receiving remittances is associated with a decline in likelihood to work for a wage.

Lastly, we look at the impacts of remittances on welfare status of the household. The results show a lower likelihood for recipient households to be positioned below 40% and 60% of per adult equivalent yearly household disposable income distribution; and a lower chance for members of recipient households to live under 2.15$ and 4.30$ per day. The evidence suggests that recipient households are doing better compared to non-recipients.

In Turkish context, our results on child schooling and child labor reveal dominance of liquidity-constraints alleviating impact of remittances for boys aged 6 to 19 and girls aged 6 to 14, and dominance of disruptive effects of migration for girls aged 15 to 19. The income effect of remittances seems to shape labor supply responses of left behind adults, and in total, recipient households are better off in terms of household welfare. In conclusion, households and their members seem to benefit from remittances with respect to developmental outcomes in the case of Turkey.

In this study, the estimated impacts of remittances on various outcomes are on the extensive margin. More can be learnt on the impacts of remittances by looking at its intensive margin effects. Further research is required in this regard to deepen the understanding of remittance impacts. Statistical inference based on IV SNP estimator requires more attention. Since it was not possible to account for intra-group error correlation with IV SNP estimator, we might have ended up with overly narrow confidence intervals and overly large t statistics. With the advancements in parallel programming and computer technology, it will be possible to overcome both problems—estimating cluster robust variance matrix and correcting for the downward bias in standard errors due to having few cluster—with IV SNP estimator in the near future.

Table 1-1 Distribution of remittance receipts and amount (average per year)

	Occurrence (% of population) (1)	Share (% of recipient households) (2)	Yearly average amount[a] (TL per adult equivalent) (3)	Average share (% of per adult equivalent household income) (4)	Average cash share (% of remittances) (5)	Average pension benefit share (% of remittances) (6)	Average in-kind share (% of remittances) (7)
Quintile 1 (poorest)	1.03	15.3	1,388.61	43.0	81.6	8.4	9.9
Quintile 2	1.47	20.4	2,375.28	40.7	74.6	16.8	8.4
Quintile 3	1.30	17.5	3,132.93	37.0	64.3	24.3	11.2
Quintile 4	1.62	22.0	4,695.64	38.0	64.2	27.2	8.4
Quintile 5 (richest)	1.62	24.5	11,297.21	46.1	41.3	53.1	5.4
Settlement[b]							
Urban	1.50	61.3	5,227.66	40.4	62.3	28.9	8.7
Rural	1.30	38.6	4,800.01	42.3	65.1	26.8	8.0
Regions[c]							
Mediterranean	1.93	16.6	5,079.31	49.3	76.3	14.5	9.1
Aegean	1.24	14.1	5,111.41	32.3	53.5	30.8	15.6
Marmara	1.04	20.0	5,200.76	34.3	49.1	45.7	5.1
Black Sea	1.03	8.8	7,068.20	48.8	54.5	38.2	7.1
Central Anatolia	1.98	25.0	5,727.84	46.4	67.6	27.2	5.1
Eastern Anatolia	1.53	8.5	2,912.36	38.6	77.7	15.2	7.0
Southeastern Anatolia	.946	6.6	2,088.89	32.9	72.9	9.6	17.4
Turkey	1.37	100	5,062.36	41.1	63.4	28.1	8.4

Notes: Quintiles are formed by ranking households from lowest to highest and dividing them in 5 groups with respect to per adult equivalent yearly household disposable income.
[a] to have comparable income values for households, TL figures are adjusted with December 2003 based CPI and moved to December 2011.
[b] communities with population above 20,000 are urban, and communities with population equal to or less than 20,000 are rural.
[c] refers to 7 geographical regions of Turkey.

Table 1-2 Descriptive statistics of key variables for households with a child aged 6 to 19

		Number of observations	Recipient households		Non-recipient households	
			Mean	Standard deviation	Mean	Standard deviation
Households		50,136	.0128		.9872	
Outcome variables						
School attendance of children 6 to 14						
	Males	25,430	.923	.266	.898	.301
	Females	24,166	.888	.315	.867	.338
School attendance of children 15 to 19						
	Males	14,680	.617	.487	.561	.496
	Females	14,483	.481	.500	.475	.499
Child illiteracy (ages 6-14 years)						
	Males	25,430	.047	.213	.073	.260
	Females	24,166	.073	.261	.082	.275
Labor force participation of females 15 to 19						
	Any kind	14,484	.108	.312	.175	.379
	Wage work	14,484	.031	.174	.084	.277
	Unpaid family work	14,484	.077	.268	.089	.285
	Self-employment	14,484	0	0	.001	.040
Labor force participation of males 15 to 19						
	Any kind	14,680	.234	.424	.297	.457
	Wage work	14,680	.193	.396	.185	.388
	Unpaid family work	14,680	.035	.186	.105	.307
	Self-employment	14,680	.005	.071	.006	.081
Household variables						
Adult equivalent household size[a]		78,759	2.54	.771	2.78	.848
Adult equivalent yearly disposable income[b] (remittances included)		78,759	8,473.06	6,109.67	8,858.61	9,617.16
Parental educational attainment						
	Illiterate	78,758	.116	.320	.054	.226
	Junior high and below	78,758	.705	.456	.670	.470
	High school	78,758	.141	.348	.182	.386
	Above high school	78,758	.036	.187	.092	.290
Age of household head						
	Below 30	78,745	.032	.177	.016	.128
	Between 30 and 50	78,745	.799	.400	.806	.394
	Above 50	78,745	.168	.374	.176	.381
Married household head		78,745	.929	.256	.962	.190
Female household head		78,745	.406	.491	.065	.247
Ownership of piped water system		78,759	.952	.212	.935	.245
Ownership of natural gas system		78,759	.093	.290	.135	.342
Rural area[c]		78,759	.371	.483	.346	.475
Number of children aged 0 to 5		78,759	.317	.590	.417	.723

Table 1-2 (continued)

Number of school age children (ages 6-19 years)	78,759	2.32	1.17	2.42	1.35
Number of adults (ages 20-64 years)	78,759	1.96	.970	2.33	.889
Region level variables					
Regional migration rate in 1985	78,759	.0164	.007	.0151	.007
Regional development index in 1973	78,759	.863	.648	1.00	.756
Length of road per 1 km^2 in 1980	78,759	.082	.023	.086	.027
Share of asphalt roads in 1985	78,759	.143	.155	.152	.178
Number of schools per 1000 children aged 6 to 16 in 1985	78,759	3.90	1.42	3.85	1.61
Gini of household income	78,759	.371	.025	.370	.027
Gross enrollment ratio of males aged 6 to 10 in 1985 (only for outcomes of males aged 6 to 14)	25,430	1.04	.110	1.06	.159
Gross enrollment ratio of females aged 6 to 10 in 1985 (only for outcomes of females aged 6 to 14)	24,166	.939	.252	.983	.247
Net enrollment ratio of males aged 15 to 19 (only for outcomes of males aged 15 to 19)	14,680	.576	.056	.577	.061
Net enrollment ratio of females aged 15 to 19 (only for outcomes of females aged 15 to 19)	14,483	.468	.099	.477	.118
Share of men aged 25 to 64 with degree[d]					
Below high school	29,163	.649	.047	.642	.049
High school	29,163	.198	.031	.200	.031
Above high school	29,163	.117	.031	.120	.037
Unemployment for males 15 years old or older[d] (in percentages)	29,163	11.5	2.75	10.8	2.71
Share of men aged 15-64 working in agricultural sector[d]	29,163	.143	.063	.137	.071
Share of men aged 15-64 working in private sector[d]	29,163	.593	.052	.593	.058

Notes: [a] to estimate adult equivalent household size a measure by OECD is implemented: for the first adult in the household the count number is 1, for other household members over age 14 the count number is 0.5, for household members below 14 years of age the count number is 0.3.

[b] to have comparable income values for households, TL figures are adjusted with December 2003 based CPI and moved to December 2011.

[c] communities with population above 20,000 are urban, and communities with population equal to or less than 20,000 are rural.

[d] calculated for the sample consisting of oldest children (ages 15-19 years) of household heads.

Table 1-3 Descriptive Statistics of key variables for households with an adult aged 20 to 64

		Number of observations	Recipient households		Non-recipient households	
			Mean	Standard deviation	Mean	Standard deviation
Households		92,893	.0146		.9854	
Individual variables						
Labor force participation of females 20 to 24						
	Any kind	15,630	.292	.455	.284	.451
	Wage work	15,630	.158	.366	.171	.377
	Unpaid family work	15,630	.118	.324	.103	.304
	Self-employment	15,630	.014	.121	.009	.095
Labor force participation of males 20 to 24						
	Any kind	11,661	.524	.501	.616	.486
	Wage work	11,661	.377	.486	.422	.494
	Unpaid family work	11,661	.097	.298	.141	.348
	Self-employment	11,661	.048	.216	.052	.223
Labor force participation of females 25 to 49						
	Any kind	68,862	.286	.452	.304	.460
	Wage work	68,862	.120	.325	.146	.353
	Unpaid family work	68,862	.100	.301	.112	.315
	Self-employment	68,862	.065	.247	.045	.208
Labor force participation of males 25 to 49						
	Any kind	63,991	.763	.425	.892	.309
	Wage work	63,991	.495	.500	.609	.487
	Unpaid family work	63,991	.041	.199	.026	.159
	Self-employment	63,991	.226	.418	.257	.437
Labor force participation of females 50 to 64						
	Any kind	24,116	.197	.398	.229	.420
	Wage work	24,116	.044	.207	.037	.189
	Unpaid family work	24,116	.100	.301	.150	.357
	Self-employment	24,116	.051	.221	.041	.200
Labor force participation of males 50 to 64						
	Any kind	24,185	.380	.486	.568	.495
	Wage work	24,185	.144	.352	.221	.414
	Unpaid family work	24,185	.006	.079	.008	.091
	Self-employment	24,185	.229	.421	.338	.473
Educational attainment						
	Illiterate	208,445	.141	.348	.096	.294
	Junior high and below	208,445	.621	.485	.623	.484
	High school	208,445	.176	.381	.188	.391
	Above high school	208,445	.061	.239	.091	.288
Married		208,445	.774	.418	.825	.379
Household head		208,445	.424	.494	.406	.491
Household variables						

Table 1-3 (continued)

Max. household educational attainment					
Illiterate	208,445	.009	.097	.005	.070
Junior high and below	208,445	.534	.498	.487	.499
High school	208,445	.328	.469	.334	.471
Above high school	208,445	.127	.333	.173	.378
Adult equivalent household size[a]	208,445	2.39	.828	2.51	.887
Adult equivalent yearly disposable income[b] (remittances included)	208,445	11,095.24	8,647.64	10,853.22	11,504.26
Number of children aged 0 to 5	208,445	.323	.597	.446	.743
Number of school age children (ages 6-19 years)	208,445	1.11	1.28	1.20	1.36
Number of adults (ages 20-64 years)	208,445	2.44	1.07	2.67	1.13
Ownership of piped water system	208,445	.974	.158	.956	.204
Ownership of natural gas system	208,445	.147	.355	.163	.370
Rural[c]	208,445	.380	.485	.337	.472
Region level variables					
Regional migration rate in 1985	208,445	.0174	.006	.0160	.006
Regional development index in 1973	208,445	.915	.659	1.06	.765
Length of road per 1 km^2 in 1980	208,445	.084	.023	.089	.027
Share of asphalt roads in 1985	208,445	.155	.153	.164	.179
Number of schools per 1000 children aged 6 to 16 in 1985	208,445	3.92	1.43	3.92	1.72
Gini of household income	208,445	.367	.026	.367	.026
Share of men aged 25 to 64 with degree[d]					
Below high school	208,445	.651	.046	.642	.051
High school	208,445	.199	.029	.202	.030
Above high school	208,445	.119	.030	.124	.037
Unemployment for males 15 years old or older[d] (in percentages)	208,445	11.0	2.68	10.5	2.63
Share of men aged 15-64 working in agricultural sector[d]	208,445	.139	.062	.131	.072
Share of men aged 15-64 working in private sector[d]	208,445	.600	.051	.599	.056

Notes: [a] to estimate adult equivalent household size a measure by OECD is implemented: for the first adult in the household the count number is 1, for other household members over age 14 the count number is 0.5, for household members below 14 years of age the count number is 0.3.
[b] to have comparable income values for households TL figures are adjusted with December 2003 based CPI and moved to December 2011.
[c] communities with population above 20,000 are urban, and communities with population equal to or less than 20,000 are rural.
[d] calculated for the sample consisting of oldest adults by age groups 20-24, 25-49, and 50-64 in households.

Table 1-4 Descriptive statistics of key variables for households

	Number of observations	Recipient households Mean	Recipient households Standard deviation	Non-recipient households Mean	Non-recipient households Standard deviation
Households	98,567	0.0155		0.9845	
Households below					
40 % of the median of the per adult equivalent yearly household disposable income	98,567	.080	.272	.112	.315
50 % of the median of the per adult equivalent yearly household disposable income	98,567	.124	.330	.172	.378
60 % of the median of the per adult equivalent yearly household disposable income	98,567	.193	.395	.237	.425
70 % of the median of the per adult equivalent yearly household disposable income	98,567	.260	.438	.305	.460
50 % of the median of the per adult equivalent monthly household expenditure	98,567	.117	.321	.155	.362
Daily per adult equivalent expenditure levels of 1$	98,567	0	0	.0001	.010
Daily per adult equivalent expenditure levels of 2,15$	98,567	.001	.036	.002	.051
Daily per adult equivalent expenditure levels of 4,30$	98,567	.017	.129	.031	.175
Household variables					
Max. household educational attainment					
Illiterate	98,567	.037	.189	.021	.145
Junior high and below	98,567	.598	.490	.520	.499
High school	98,567	.264	.441	.298	.457
Above high school	98,567	.100	.300	.159	.366
Age of household head					
Below 30	98,567	.068	.251	.078	.269
Between 30 and 50	98,567	.402	.490	.514	.499
Above 50	98,567	.529	.499	.406	.491
Married household head	98,567	.837	.368	.889	.313
Female household head	98,557	.336	.472	.109	.312
Adult equivalent household size[a]	98,567	2.11	.769	2.29	.822
Adult equivalent yearly disposable income[b] (remittances included)	98,567	11,807.96	9,478.14	11,071.62	12,099.68
Adult equivalent monthly expenditure[b]	98,567	942.61	786.08	850.61	760.62
Number of children aged 0 to 5	98,567	.274	.569	.401	.700
Number of school age children (ages 6-19 years)	98,567	.988	1.24	1.12	1.32
Number of adults (ages 20-64 years)	98,567	1.80	1.14	2.23	1.10
Ownership of piped water system	98,567	.977	.147	.958	.199
Ownership of natural gas system	98,567	.153	.360	.165	.371
Rural[c]	98,567	.386	.487	.337	.472
Region level variables					
Regional migration rate in 1985	98,567	.0176	.006	.0161	.006
Regional development index in 1973	98,567	.930	.676	1.07	.759

Table 1-4 (continued)

Length of road per 1 km^2 in 1980	98,567	.085	.024	.089	.026
Share of asphalt roads in 1985	98,567	.161	.157	.165	.177
Number of schools per 1000 children aged 6 to 16 in 1985	98,567	3.94	1.48	3.93	1.74
Gini of household income	98,567	.366	.025	.366	.026
Share of men aged 25 to 64 with degree[d]					
Below high school	98,567	.651	.046	.642	.051
High school	98,567	.199	.029	.202	.030
Above high school	98,567	.120	.030	.125	.037
Unemployment for males 15 years old or older[d] (in percentages)	98,567	10.8	2.67	10.4	2.62
Share of men aged 15-64 working in agricultural sector[d]	98,567	.138	.062	.131	.071
Share of men aged 15-64 working in private sector[d]	98,567	.602	.050	.600	.055

Notes: [a] to estimate adult equivalent household size a measure by OECD is implemented: for the first adult in the household the count number is 1, for other household members over age 14 the count number is 0.5, for household members below 14 years of age the count number is 0.3.
[b] to have comparable income and expenditure values for households, TL figures are adjusted with December 2003 based CPI and moved to December 2011.
[c] communities with population above 20,000 are urban, and communities with population equal to or less than 20,000 are rural.
[d] calculated for the sample consisting of households.

Table 1-5 First stage estimations (child sample)

	Samples of children of household head (aged between 6 and 19 years old)							
	Males				Females			
	6-14-years-olds		15-19-years-olds		6-14-years-olds		15-19-years-olds	
	Probit	OLS	Probit	OLS	Probit	OLS	Probit	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Individual level covariate								
Oldest child	-0.0078	-0.0007	-0.0707	-0.0031	-0.1192**	-0.0044***	-0.1058	-0.0036
	(0.0505)	(0.0011)	(0.0833)	(0.0027)	(0.0545)	(0.0016)	(0.0937)	(0.0029)
Affected by educational system reform[a]			-0.0232	-0.0010			-0.1025	-0.0038
			(0.0927)	(0.0027)			(0.0918)	(0.0030)
Household level covariates								
Parental educational attainment								
Junior high and below	-0.1412	-0.0112	-0.2025	-0.0115*	-0.1879*	-0.0176**	-0.2048*	-0.0139*
	(0.1172)	(0.0068)	(0.1238)	(0.0070)	(0.0998)	(0.0085)	(0.1055)	(0.0075)
High school	-0.3311**	-0.0179**	-0.2517*	-0.0140*	-0.2490**	-0.0211**	-0.2711	-0.0175*
	(0.1494)	(0.0078)	(0.1524)	(0.0078)	(0.1153)	(0.0093)	(0.1662)	(0.0094)
Above high school	-0.4943***	-0.0215***	-0.6114***	-0.0223***	-0.4856***	-0.0258***	-0.6400***	-0.0250***
	(0.1390)	(0.0075)	(0.2306)	(0.0083)	(0.1493)	(0.0096)	(0.2154)	(0.0091)
Age of household head								
Between 30 and 50	0.0352	-0.0035	2.7964***	0.0323***	-0.1910*	-0.0151*	2.9404***	0.0250***
	(0.1305)	(0.0062)	(0.2150)	(0.0093)	(0.1144)	(0.0085)	(0.2130)	(0.0069)
Above 50	0.1776	0.0036	2.6907***	0.0296***	-0.2970*	-0.0156*	2.8527***	0.0232***
	(0.1227)	(0.0053)	(0.2143)	(0.0090)	(0.1582)	(0.0088)	(0.2126)	(0.0073)
Married household head	0.3612***	0.0088	0.4106***	0.0123**	0.3045***	0.0010	0.2484***	0.0051
	(0.1225)	(0.0058)	(0.1476)	(0.0051)	(0.1174)	(0.0088)	(0.0893)	(0.0054)
Ownership of piped water system	0.0469	0.0016	0.0559	0.0020	0.1517	0.0044	0.0284	0.0018
	(0.1507)	(0.0040)	(0.1567)	(0.0039)	(0.1682)	(0.0044)	(0.1526)	(0.0048)
Ownership of natural gas system	-0.1686**	-0.0032**	0.1587**	0.0046*	-0.0964	-0.0009	0.0453	0.0015
	(0.0788)	(0.0016)	(0.0645)	(0.0025)	(0.0962)	(0.0021)	(0.0995)	(0.0028)
Rural area[b]	0.0000	0.0000	0.0629	0.0016	-0.0596	-0.0020	0.0849	0.0023
	(0.0614)	(0.0020)	(0.0839)	(0.0031)	(0.0544)	(0.0016)	(0.0751)	(0.0026)
Number of children aged 0 to 5	-0.1608***	-0.0037***	-0.0078	0.0004	-0.0258	-0.0007	0.0017	0.0002
	(0.0553)	(0.0013)	(0.0560)	(0.0015)	(0.0366)	(0.0008)	(0.0559)	(0.0014)
Number of male children (ages 6-19 years)	-0.0496	-0.0009	-0.0799**	-0.0023**	-0.0415	-0.0011	-0.0880**	-0.0026**
	(0.0355)	(0.0008)	(0.0356)	(0.0010)	(0.0277)	(0.0007)	(0.0360)	(0.0011)
Number of female children (ages 6-19 years)	-0.0807**	-0.0019*	-0.0859**	-0.0024**	-0.0189	-0.0002	-0.0749**	-0.0022**
	(0.0384)	(0.0010)	(0.0357)	(0.0010)	(0.0298)	(0.0008)	(0.0363)	(0.0010)
Number of adult males (ages 20-64 years)	-0.7746***	-0.0238***	-0.4922***	-0.0132***	-0.8495***	-0.0225***	-0.5818***	-0.0161***
	(0.1092)	(0.0053)	(0.0855)	(0.0032)	(0.1011)	(0.0055)	(0.1041)	(0.0036)
Number of adult females (ages 20-64 years)	0.1867***	0.0091***	0.0151	0.0013	0.1976***	0.0085***	0.0580	0.0035
	(0.0483)	(0.0019)	(0.0913)	(0.0029)	(0.0445)	(0.0021)	(0.0663)	(0.0021)
Regional level covariates								

Table 1-5 (continued)

Regional development index in 1973	-0.4274*** (0.1654)	-0.0164** (0.0068)	-0.0019 (0.2035)	0.0009 (0.0061)	-0.2755 (0.1750)	-0.0079 (0.0079)	-0.2249 (0.3649)	-0.0080 (0.0093)
Length of road per 1 km^2 in 1980	0.7726 (2.793)	0.0407 (0.1036)	-3.2188 (3.3402)	-0.1311 (0.1312)	1.090 (3.657)	0.0620 (0.1547)	0.2778 (3.3941)	0.0635 (0.1242)
Share of asphalt roads in 1985	-0.7443 (0.8442)	-0.0213 (0.0352)	-0.4861 (0.8264)	-0.0057 (0.0343)	-0.2639 (1.015)	0.0014 (0.0441)	0.7782 (1.7740)	0.0591 (0.0543)
Interaction of length and share of roads	7.614 (7.354)	0.2507 (0.2669)	4.5545 (7.8000)	0.1021 (0.3087)	3.582 (8.006)	-0.0337 (0.3370)	1.2308 (15.8695)	-0.1897 (0.4709)
Number of schools per 1000 children aged 6 to 16 in 1985	-0.0753* (0.0458)	-0.0023* (0.0013)	0.0378 (0.0444)	0.0022 (0.0015)	0.0106 (0.0461)	0.0001 (0.0015)	-0.0280 (0.0724)	-0.0002 (0.0017)
Gross enrollment ratio of children aged 6 to 10 in 1985[c]	-0.0364 (0.2680)	0.0021 (0.0105)			-0.0643 (0.1687)	-0.0079 (0.0090)		
Net enrollment ratio of children aged 15 to 19[d]			1.3211 (0.9557)	0.0197 (0.0382)			0.5629 (1.0712)	0.0106 (0.0319)
Gini of household income	0.7783 (1.215)	0.0362 (0.0391)	0.6845 (1.7896)	0.0072 (0.0757)	1.918 (1.394)	0.0792 (0.0523)	-0.4471 (1.6697)	0.0151 (0.0750)
Share of men aged 25 to 64 with degree[e]								
High school			0.0642 (1.7807)	0.0425 (0.0724)			0.4243 (1.7705)	0.0377 (0.0596)
Above high school			-1.7005 (2.1245)	-0.0567 (0.0787)			1.5902 (2.7412)	0.0271 (0.0799)
Unemployment for males 15 years old or older[e] (in percentages)			0.0756*** (0.0184)	0.0029*** (0.0010)			0.0714*** (0.0250)	0.0024** (0.0010)
Share of men aged 15-64 working in agricultural sector[e]			1.8503* (1.0592)	0.0722 (0.0477)			2.8000* (1.6529)	0.0903 (0.0672)
Share of men aged 15-64 working in private sector[e]			0.1382 (0.7362)	-0.0036 (0.0265)			-0.7598 (1.3526)	-0.0340 (0.0423)
Year fixed effects								
2004	0.0859 (0.1227)	0.0025 (0.0036)	0.1941* (0.1107)	0.0074 (0.0045)	0.0460 (0.1126)	0.0023 (0.0037)	0.1376 (0.1422)	0.0044 (0.0044)
2005	0.0000 (0.1093)	-0.0005 (0.0028)	0.2073* (0.1202)	0.0064 (0.0045)	0.0299 (0.0839)	0.0008 (0.0023)	0.2149 (0.1355)	0.0071 (0.0049)
2006	0.0883 (0.1287)	0.0015 (0.0037)	0.0817 (0.1339)	0.0020 (0.0039)	0.0225 (0.1201)	0.0000 (0.0031)	0.1221 (0.1745)	0.0037 (0.0050)
2007	0.1095 (0.1090)	0.0020 (0.0031)	0.0729 (0.1381)	0.0015 (0.0037)	0.1221 (0.1107)	0.0035 (0.0035)	0.1953 (0.1538)	0.0058 (0.0049)
2008	0.2849** (0.1171)	0.0096* (0.0052)	0.3288** (0.1341)	0.0136** (0.0063)	0.0322 (0.1302)	0.0008 (0.0036)	0.2988** (0.1420)	0.0097* (0.0055)
2009	0.1617* (0.0953)	0.0046 (0.0028)	0.1706 (0.1231)	0.0060 (0.0042)	0.0462 (0.0961)	0.0009 (0.0027)	0.2460* (0.1312)	0.0070* (0.0040)
2010	0.2442** (0.1207)	0.0080* (0.0045)	0.0569 (0.1403)	0.0014 (0.0039)	0.1556 (0.1125)	0.0049 (0.0039)	0.2431* (0.1365)	0.0070 (0.0044)

Table 1-5 (continued)

2011	-0.0446	-0.0007	-0.1294	-0.0028	-0.0624	-0.0016	-0.0692	-0.0007
	(0.1049)	(0.0021)	(0.1375)	(0.0032)	(0.1105)	(0.0026)	(0.1803)	(0.0041)
Constant	-1.803***	0.0291	-6.8426***	-0.0720	-2.527***	0.0236	-5.6313***	-0.0333
	(0.6490)	(0.0240)	(1.1263)	(0.0439)	(0.7318)	(0.0278)	(1.0083)	(0.0299)
Instrumental variable								
Regional migration rate in 1985	19.263***	0.8016***	22.6797***	1.0461***	22.374***	0.9848***	11.2895	0.5672*
	(3.575)	(0.1655)	(3.9424)	(.1377)	(4.225)	(0.1805)	(7.6999)	(.3042)
Weak identification test statistics								
p-value of the Wald test for the excluded instrument	0.000		0.000		0.000		0.143	
Effective F statistic		24.40		59.94		30.93		3.62
Number of observations	25,426		14,677		24,164		14,478	

Notes: Dependent variable: child lives in remittance receiving household

We use "ivreg2" command by Baum et al. (2010) to estimate OLS first stages. Stata's "ivregress" command does not take into account clustered nature of the observations in first stage regression. Cluster robust standard errors are in parenthesis. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in OLS regressions where G is the number of clusters, N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivreg2" command for IV 2SLS models, and uses standard normal distribution as basis for p-value calculations in probit models with small sample modifications.

* Significant at 10%; ** significant at 5%; *** significant at 1%

[a,e] Only applicable to children aged 15 to 19.

[b] Communities with population above 20,000 are urban, and communities with population equal to or less than 20,000 are rural.

[c] Historical enrollment rates of males being reported for 6-14-years-old boys samples and historical enrollment rates of females being reported for 6-14-years-old girls samples.

[d] Average enrollment rates of males being reported for 15-19-years-old boys samples and average enrollment rates of females being reported for 15-19-years-old girls samples.

Table 1-6 First stage estimations (samples of working age adult males)

	Males					
	20-24-years-olds		25-49-years-olds		50-64-years-olds	
	Probit	OLS	Probit	OLS	Probit	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Individual level covariate						
Educational attainment						
Junior high and below	-0.1326	-0.0059	-0.1636*	-0.0050	-0.0870	-0.0026
	(0.2152)	(0.0087)	(0.0931)	(0.0033)	(0.1102)	(0.0037)
High school	-0.1409	0.0121	-0.1996*	-0.0059	-0.2216	-0.0065
	(0.3031)	(0.0121)	(0.1068)	(0.0036)	(0.1679)	(0.0053)
Above high school	-0.0852	-0.0062	-0.2737*	-0.0076*	-0.3164	-0.0090
	(0.3397)	(0.0128)	(0.1558)	(0.0046)	(0.2042)	(0.0056)
Household head	-0.1663	-0.0030	-0.3519***	-0.0099***	-0.4009***	-0.0151***
	(0.1600)	(0.0050)	(0.0494)	(0.0018)	(0.0958)	(0.0052)
Married	-0.1893*	-0.0065*	-0.0085	-0.0002	-0.1135	-0.0051
	(0.1098)	(0.0033)	(0.0659)	(0.0019)	(0.1098)	(0.0048)
Household level covariates						
Max. household educational attainment						
Junior high and below	-0.6453	-0.0534	0.1746	0.0049	0.3138	0.0108
	(0.5627)	(0.0727)	(0.4070)	(0.0096)	(0.2495)	(0.0080)
High school	-0.6202	-0.0520	0.2941	0.0077	0.2717	0.0084
	(0.6353)	(0.0742)	(0.4191)	(0.0100)	(0.2737)	(0.0086)
Above high school	-0.8964	-0.0582	0.2754	0.0074	0.1692	0.0060
	(0.6128)	(0.0740)	(0.4163)	(0.0099)	(0.2731)	(0.0085)
Ownership of piped water system	0.0875	0.0024	-0.0083	-0.0001	0.1528	0.0033
	(0.1862)	(0.0037)	(0.1264)	(0.0024)	(0.1581)	(0.0040)
Ownership of natural gas system	0.2176***	0.0060***	-0.0264	-0.0005	0.2073***	0.0076***
	(0.0702)	(0.0018)	(0.0590)	(0.0012)	(0.0600)	(0.0021)
Rural area[a]	0.1745**	0.0052*	0.0526	0.0013	0.0580	0.0020
	(0.0728)	(0.0028)	(0.0458)	(0.0011)	(0.0757)	(0.0026)
Number of children aged 0 to 5	-0.0219	-0.0003	-0.0761***	-0.0015**	-0.0701	-0.0015
	(0.0524)	(0.0013)	(0.0285)	(0.0006)	(0.0490)	(0.0010)
Number of male children (ages 6-19 years)	0.0525	0.0008	0.0189	0.0004	-0.0135	-0.0005
	(0.0536)	(0.0015)	(0.0192)	(0.0004)	(0.0292)	(0.0008)
Number of female children (ages 6-19 years)	-0.0079	-0.0001	-0.0043	-0.0002	-0.0872**	-0.0024***
	(0.0380)	(0.0011)	(0.0204)	(0.0004)	(0.0344)	(0.0009)
Number of adult males (ages 20-64 years)	-0.4039***	-0.0105***	-0.1884***	-0.0047***	-0.2197***	-0.0054***
	(0.0729)	(0.0026)	(0.0308)	(0.0008)	(0.0390)	(0.0010)
Number of adult females (ages 20-64 years)	0.1571***	0.0056***	0.0558*	0.0014	-0.0051	-9.03e-06
	(0.0446)	(0.0019)	(0.0312)	(0.0009)	(0.0343)	(0.0010)
Regional level covariates						
Regional development index in 1973	0.2250	0.0019	-0.0233	0.0000	0.0042	-0.0022
	(0.1583)	(0.0040)	(0.2546)	(0.0054)	(0.2556)	(0.0073)
Length of road per 1 km^2 in 1980	2.6613	0.0903	-5.1029	-0.1326*	-2.0894	-0.0329
	(2.3539)	(0.0725)	(3.2663)	(0.0700)	(2.8393)	(0.1220)
Share of asphalt roads in 1985	1.4162**	0.0417	0.1401	0.0075	1.5091	0.0666
	(0.7112)	(0.0293)	(0.9335)	(0.0220)	(1.0088)	(0.0458)
Interaction of length and share of roads	-25.394***	-0.6606***	2.9366	0.0596	-11.4932	-0.4440
	(6.4629)	(0.2200)	(9.5511)	(0.2095)	(10.0899)	(0.3392)
Number of schools per 1000 children aged 6 to 16 in 1985	0.0248	0.0006	0.0289	0.0007	-0.0830*	-0.0009
	(0.0413)	(0.0008)	(0.0399)	(0.0009)	(0.0469)	(0.0016)
Gini of household income	6.0083***	0.1654***	-2.0898	-0.0695	-2.3102	-0.0397
	(1.8697)	(0.0530)	(1.7929)	(0.0505)	(1.8496)	(0.0894)
Share of men aged 25 to 64 with degree						
High school	1.7783	0.0381	1.0173	0.0140	1.8211	0.0407
	(1.3485)	(0.0373)	(1.4286)	(0.0371)	(1.4044)	(0.0603)
Above high school	-6.8872***	-0.1984***	-0.4048	-0.0060	-2.8867	-0.1074
	(1.8205)	(0.0481)	(2.3287)	(0.0565)	(2.3963)	(0.0931)
Unemployment for males 15 years old or older (in percentages)	0.0135	0.0008***	0.0541***	0.0014***	0.0590***	0.0022***
	(0.0119)	(0.0002)	(0.0183)	(0.0005)	(0.0194)	(0.0007)
Share of men aged 15-64 working in agricultural sector	-0.6011	-0.0155	1.5327	0.0517*	2.3093**	0.0694*
	(1.0604)	(0.0291)	(1.1070)	(0.0289)	(0.9903)	(0.0366)
Share of men aged 15-64 working in private sector	2.1418***	0.0335*	0.5935	-0.0033	-0.3352	-0.0400
	(0.7869)	(0.0202)	(0.8493)	(0.0208)	(0.9262)	(0.0420)

Table 1-6 (continued)

Year fixed effects						
2004	0.1250 (0.1294)	0.0045 (0.0040)	0.0740 (0.1335)	0.0010 (0.0026)	0.0157 (0.1496)	0.0002 (0.0046)
2005	0.2580** (0.1282)	0.0057 (0.0036)	0.2284*** (0.0812)	0.0042** (0.0017)	0.1147 (0.0954)	0.0032 (0.0032)
2006	0.0465 (0.1622)	0.0016 (0.0040)	0.2096*** (0.0799)	0.0037** (0.0016)	0.0524 (0.0959)	0.0017 (0.0030)
2007	0.0249 (0.1531)	0.0000 (0.0036)	0.1824** (0.0859)	0.0031* (0.0017)	-0.0341 (0.0968)	-0.0007 (0.0026)
2008	0.3101*** (0.1062)	0.0104** (0.0048)	0.3487*** (0.0798)	0.0081*** (0.0025)	0.1305 (0.0994)	0.0050 (0.0040)
2009	0.2082* (0.1264)	0.0056 (0.0041)	0.3367*** (0.0914)	0.0076*** (0.0027)	0.2329*** (0.0835)	0.0090** (0.0036)
2010	0.3242*** (0.1078)	0.0107** (0.0044)	0.3300*** (0.0842)	0.0072*** (0.0025)	0.1331 (0.1063)	0.0051 (0.0044)
2011	-0.0382 (0.1447)	-0.0009 (0.0027)	0.0979 (0.0891)	0.0015 (0.0015)	-0.2662*** (0.0935)	-0.0061*** (0.0019)
Constant	-5.3495*** (1.2984)	-0.0245 (0.0804)	-2.7225** (1.1864)	0.0171 (0.0291)	-1.6470 (1.1632)	0.0283 (0.0525)
Instrumental variable						
Regional migration rate in 1985	45.0946*** (4.7975)	1.6112*** (0.1742)	19.7422*** (5.0222)	0.6355*** (0.1658)	25.0418*** (5.7219)	1.2294*** 0.4210
Weak identification test statistics						
p-value of the Wald test for the excluded instrument	0.000		0.000		0.000	
Effective F statistic		88.86		15.28		8.87
Number of observations	11,661		63,991		24,185	

Notes: Dependent variable: working age male lives in remittance receiving household

We use "ivreg2" command by Baum et al. (2010) to estimate OLS first stages. Stata's "ivregress" command does not take into account clustered nature of the observations in first stage regressions.

Cluster robust standard errors are in parenthesis. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in OLS regressions where G is the number of clusters, N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivreg2" command for IV 2SLS models, and uses standard normal distribution as basis for p-value calculations in probit models with small sample modifications.

* Significant at 10%; ** significant at 5%; *** significant at 1%

[a] Communities with population above 20,000 are urban, and communities with population equal to or less than 20,000 are rural.

Table 1-7 First stage estimations (samples of working age adult females)

	Females					
	20-24-years-olds		25-49-years-olds		50-64-years-olds	
	Probit	OLS	Probit	OLS	Probit	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Individual level covariate						
Educational attainment						
Junior high and below	0.1437 (0.1314)	0.0038 (0.0029)	-0.0662 (0.0479)	-.0022 (.0019)	-0.1399*** (0.0480)	-0.0078** (0.0031)
High school	0.1660 (0.1672)	0.0028 (0.0036)	0.0057 (0.0633)	.0004 (.0024)	-0.2517* (0.1476)	-0.0133* (0.0069)
Above high school	0.4358** (0.2194)	0.0086* (0.0050)	-0.2251** (0.1100)	-.0061** (.0030)	-0.2461** (0.1125)	-0.0138** (0.0061)
Household head	0.4055** (0.1851)	0.0425* (0.0255)	0.7574*** (0.0662)	.0608*** (.0108)	0.2549*** (0.0751)	0.0163*** (0.0056)
Married	0.0928 (0.1191)	0.0033 (0.0037)	0.2915*** (0.0645)	.0186*** (.0048)	0.2150*** (0.0717)	0.0123** (0.0048)
Household level covariates						
Max. household educational attainment						
Junior high and below	-0.1732 (0.5488)	-0.0018 (0.0267)	-0.0526 (0.1759)	-0.0095 (0.0129)	0.2794** (0.1316)	0.0137** (0.0069)
High school	-0.3247 (0.5231)	-0.0054 (0.0259)	-0.0994 (0.1975)	-0.0116 (0.0137)	0.3079** (0.1229)	0.0150** (0.0065)
Above high school	-0.5579 (0.5496)	-0.0101 (0.0264)	-0.2082 (0.1692)	-0.0150 (0.0127)	0.2571** (0.1090)	0.0135** (0.0060)
Ownership of piped water system	0.3347 (0.2537)	0.0071* (0.0040)	0.1880 (0.1289)	0.0050 (0.0034)	0.1858 (0.1618)	0.0057 (0.0051)
Ownership of natural gas system	0.2253*** (0.0816)	0.0063** (0.0029)	0.0642 (0.0417)	0.0023 (0.0014)	0.1710** (0.0850)	0.0088** (0.0039)
Rural area[a]	0.0476 (0.0687)	0.0015 (0.0022)	0.0586 (0.0422)	0.0018 (0.0015)	0.0614 (0.0813)	0.0028 (0.0039)
Number of children aged 0 to 5	-0.0780 (0.0523)	-0.0019 (0.0014)	-0.0813*** (0.0216)	-0.0024*** (0.0006)	-0.0373 (0.0386)	-0.0011 (0.0013)
Number of male children (ages 6-19 years)	0.0376 (0.0358)	0.0008 (0.0009)	-0.0155 (0.0197)	-0.0007 (0.0006)	0.0376 (0.0303)	0.0016 (0.0013)
Number of female children (ages 6-19 years)	0.0348 (0.0357)	0.0013 (0.0012)	-0.0387** (0.0188)	-0.0014** (0.0006)	0.0054 (0.0394)	0.0002 (0.0002)
Number of adult males (ages 20-64 years)	-0.3434*** (0.0633)	-0.0090*** (0.0025)	-0.2318*** (0.0320)	-0.0078*** (0.0012)	-0.2299*** (0.0293)	-0.0090*** (0.0016)
Number of adult females (ages 20-64 years)	0.1351** (0.0567)	0.0057** (0.0027)	0.1664*** (0.0231)	0.0077*** (0.0015)	0.0348 (0.0328)	0.0020 (0.0017)
Regional level covariates						
Regional development index in 1973	0.0466 (0.3323)	-0.0026 (0.0076)	-0.1139 (0.2164)	-0.0035 (0.0068)	0.0725 (0.2732)	0.0002 (0.0110)
Length of road per 1 km^2 in 1980	-0.7669 (3.2960)	0.0461 (0.1533)	-2.8952 (2.9692)	-0.0737 (0.1204)	-2.9552 (3.2934)	-0.1415 (0.1596)
Share of asphalt roads in 1985	2.4339** (1.1614)	0.1265** (0.0596)	0.3916 (0.9078)	0.0351 (0.0437)	1.0914 (0.9840)	0.0667 (0.0538)
Interaction of length and share of roads	-16.8213 (11.5335)	-0.7982* (0.4331)	-0.3575 (8.9903)	-0.1606 (0.3628)	-9.2204 (10.1774)	-0.4401 (0.4253)
Number of schools per 1000 children aged 6 to 16 in 1985	0.0742 (0.0703)	0.0010 (0.0021)	0.0225 (0.0406)	0.0010 (0.0014)	0.0114 (0.0517)	0.0005 (0.0024)
Gini of household income	3.5253 (3.2268)	0.0657 (0.1275)	0.1182 (1.7300)	0.0139 (0.0822)	-1.1431 (2.2170)	-0.0876 (0.1252)
Share of men aged 25 to 64 with degree						
High school	3.9298** (1.8764)	0.1237* (0.0691)	1.6608 (1.2507)	0.0547 (0.0502)	0.3774 (1.6917)	0.0092 (0.0850)
Above high school	-4.1434 (3.6039)	-0.1596 (0.1210)	-1.0884 (2.1668)	-0.0600 (0.0817)	-2.4123 (2.7114)	-0.1217 (0.1272)
Unemployment for males 15 years old or older (in percentages)	0.0643*** (0.0138)	0.0020*** (0.0006)	0.0528*** (0.0185)	0.0020** (0.0008)	0.0387* (0.0227)	0.0019* (0.0011)
Share of men aged 15-64 working in agricultural sector	1.9358 (1.2014)	0.0834 (0.0549)	1.0794 (1.0462)	0.0477 (0.0409)	0.8802 (1.1632)	0.0702 (0.0623)
Share of men aged 15-64 working in private sector	0.5782 (1.0717)	-0.0483 (0.0405)	0.8494 (0.7930)	0.0036 (0.0256)	0.4924 (0.9271)	-0.0361 (0.0554)

Table 1-7 (continued)

Year fixed effects						
2004	0.1886 (0.1502)	0.0064 (0.0051)	0.0678 (0.0856)	0.0020 (0.0026)	0.1807 (0.1258)	0.0080 (0.0064)
2005	0.1769 (0.1293)	0.0046 (0.0041)	0.1470* (0.0847)	0.0036 (0.0026)	0.2330** (0.1005)	0.0097* (0.0050)
2006	0.2525* (0.1419)	0.0073 (0.0048)	0.1049 (0.0665)	0.0023 (0.0020)	0.1673* (0.0981)	0.0066 (0.0043)
2007	-0.2169 (0.1668)	-0.0039 (0.0026)	0.0834 (0.0714)	0.0018 (0.0023)	0.0880 (0.1082)	0.0034 (0.0043)
2008	0.1840 (0.1578)	0.0063 (0.0059)	0.2023*** (0.0766)	0.0061* (0.0035)	0.1157 (0.1101)	0.0050 (0.0051)
2009	0.3047*** (0.1152)	0.0107** (0.0046)	0.2205*** (0.0695)	0.0064** (0.0028)	0.3065*** (0.0736)	0.0146*** (0.0041)
2010	0.3261*** (0.1073)	0.0106*** (0.0038)	0.1895** (0.0777)	0.0049* (0.0028)	0.1933* (0.1122)	0.0079 (0.0056)
2011	-0.1155 (0.1397)	-0.0026 (0.0031)	-0.0069 (0.0603)	-0.0009 (0.0015)	-0.0611 (0.1091)	-0.0026 (0.0032)
Constant	-6.4156*** (1.9623)	-0.0677 (0.0713)	-4.2606*** (1.1248)	-0.0518 (0.0481)	-3.2195** (1.3084)	0.0058 (0.0688)
Instrumental variable						
Regional migration rate in 1985	36.9069*** (9.2353)	1.5556*** (0.4971)	21.8964*** (5.1619)	0.9977*** (0.2550)	30.9536*** (6.6546)	2.0257*** (0.5490)
Weak identification test statistics						
p-value of the Wald test for the excluded instrument	0.000		0.000		0.000	
Effective F statistic		10.18		15.92		14.16
Number of observations	15,630		68,862		24,116	

Notes: Dependent variable: working age female lives in remittance receiving household

We use “ivreg2” command by Baum et al. (2010) to estimate OLS first stages. Stata’s “ivregress” command does not take into account clustered nature of the observations in first stage regressions.

Cluster robust standard errors are in parenthesis. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in OLS regressions where G is the number of clusters, N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with “ivreg2” command for IV 2SLS models, and uses standard normal distribution as basis for p-value calculations in probit models with small sample modifications.

* Significant at 10%; ** significant at 5%; *** significant at 1%

[a] Communities with population above 20,000 are urban, and communities with population equal to or less than 20,000 are rural.

Table 1-8 First stage estimations (sample of households)

	Probit	OLS
	(1)	(2)
Household level covariates		
Max. household educational attainment		
Junior high and below	0.1497***	0.0050
	(0.0567)	(0.0031)
High school	0.1405*	0.0040
	(0.0721)	(0.0036)
Above high school	-0.0262	-0.0013
	(0.0793)	(0.0037)
Age of household head		
Between 30 and 50	-0.0535	-0.0021
	(0.0667)	(0.0027)
Above 50	0.0931	0.0049*
	(0.0671)	(0.0025)
Married household head	0.0346	-0.00008
	(0.0378)	(0.0017)
Ownership of piped water system	0.1937*	0.0058*
	(0.1169)	(0.0034)
Ownership of natural gas system	0.0997***	0.0042***
	(0.0357)	(0.0015)
Rural area[a]	0.0585	0.0024
	(0.0451)	(0.0019)
Number of children aged 0 to 5	-0.0672***	-0.0020***
	(0.0240)	(0.0006)
Number of male children (ages 6-19 years)	0.0186	0.0004
	(0.0179)	(0.0004)
Number of female children (ages 6-19 years)	-0.0058	-0.0003
	(0.0179)	(0.0006)
Number of adult males (ages 20-64 years)	-0.3753***	-0.0126***
	(0.0281)	(0.0018)
Number of adult females (ages 20-64 years)	0.0810***	0.0032**
	(0.0251)	(0.0014)
Regional level covariates		
Regional development index in 1973	-0.1614	-0.0064
	(0.2054)	(0.0069)
Length of road per 1 km^2 in 1980	-2.7158	-0.0906
	(2.5778)	(0.1136)
Share of asphalt roads in 1985	0.4675	0.0359
	(0.8592)	(0.0430)
Interaction of length and share of roads	-0.2491	-0.1150
	(8.7737)	(0.3648)
Number of schools per 1000 children aged 6 to 16 in 1985	0.0126	0.0004
	(0.0376)	0.0015
Gini of household income	0.2214	0.0024
	(1.7528)	(0.0843)
Share of men aged 25 to 64 with degree		
High school	1.6216	0.0593
	(1.1347)	(0.0483)
Above high school	-1.4915	-0.0827
	(2.0910)	(0.0856)
Unemployment for males 15 years old or older (in percentages)	0.0480***	0.0019***
	(0.0171)	(0.0007)
Share of men aged 15-64 working in agricultural sector	0.6608	0.0413
	(0.8970)	(0.0388)
Share of men aged 15-64 working in private sector	0.7352	-0.0098
	(0.7765)	(0.0297)
Year fixed effects		
2004	0.1030	0.0033
	(0.0826)	(0.0030)
2005	0.1569**	0.0047*
	(0.0708)	(0.0026)
2006	0.1378**	0.0041*
	(0.0648)	(0.0022)
2007	0.0961	0.0028
	(0.0606)	(0.0020)

Table 1-8 (continued)

2008	0.1920**	0.0071*
	(0.0782)	(0.0038)
2009	0.2606***	0.0098***
	(0.0584)	(0.0029)
2010	0.2040***	0.0069**
	(0.0701)	(0.0030)
2011	0.0223	0.0002
	(0.0523)	(0.0015)
Constant	-3.7790***	-0.0221
	(1.1009)	(0.0451)
Instrumental variable		
Regional migration rate in 1985	23.2196***	1.2389***
	(5.4267)	(.3158)
Weak identification test statistics		
p-value of the Wald test for the excluded instrument	0.000	
Effective F statistic		16.00
Number of observations	98,557	

Notes: Dependent variable: household receives remittances

We use "ivreg2" command by Baum et al. (2010) to estimate OLS first stages. Stata's "ivregress" command does not take into account clustered nature of the observations in first stage regressions.

Cluster robust standard errors are in parenthesis. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in OLS regressions where G is the number of clusters, N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivreg2" command for IV 2SLS models, and uses standard normal distribution as basis for p-value calculations in probit models with small sample modifications.

* Significant at 10%; ** significant at 5%; *** significant at 1%

[a] Communities with population above 20,000 are urban, and communities with population equal to or less than 20,000 are rural.

Table 1-9 The impact of remittances on school attendance of children aged 6 to 14

	Males				Females			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: coefficient estimates								
Remittances	0.1680	0.9714	0.4419	0.3096*	0.1407	2.5102***	0.9254*	0.4280*
	(0.1081)	(0.5938)	(0.6786)	(0.1734)	(0.1019)	(0.6875)	(0.4908)	(0.2566)
	[0.1165]	[0.6608]	[0.6276]		[0.0973]	[0.4970]	[0.4983]	
Panel B: p-values based on different rejection methods								
N(0,1)	0.1492		0.4814	0.0741	0.1483		0.0633	0.0953
t(G-1)	0.1616	0.1540	0.4879		0.1607	0.000032	0.0751	
t(G-2)	0.1621	0.1545	0.4881		0.1612	0.000036	0.0756	
t(G-L)	0.1655	0.1579	0.4899		0.1646	0.000071	0.0788	
WRE bootstrap:								
Symmetric test Rademacher		0.3844				0.0129		
Symmetric test Mammen		0.3600				0.0119		
Equal-tailed test Rademacher		0.3420				0.0238		
Equal-tailed test Mammen		0.2394				0.0208		
Restricted score bootstrap:								
Symmetric test Rademacher	0.1236		0.5170		0.1292		0.3470	
Symmetric test Mammen	0.1426		0.5211		0.1263		0.3621	
Equal-tailed test Rademacher	0.1160		0.5201		0.1246		0.3564	
Equal-tailed test Mammen	0.0726		0.4772		0.1116		0.2758	
Pairs cluster bootstrap-t							0.1000	
Panel C: test statistics								
p-values of endogeneity tests:								
Woolridge's score test		0.086				0.0001		
Wald test of ρ=0			0.6439				0.1479	
Instrument relevance:								
p-value of Wald test			0.000	0.001			0.000	0.000
Effective F statistic		24.40				30.93		
p-value- score test of normality			0.0000				0.0000	
Number of observations	25,426				24,164			

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: a dummy for the observation being the oldest child in the household, last finished schooling of the parent, dummies for marital status and age of the household head, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gross enrollment ratio of children aged 6 to 10 in 1985 by region, and gini of household income by region. Historical regional gross enrollment ratios are for historical male enrollment rates in columns 1-4, and historical female enrollment rates in columns 5-8. The dependent variable is a dummy taking value 1 if the child attends school and 0 otherwise. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26.

L is the number of exogenous regressors that are invariant within clusters and includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gross enrollment ratio of children aged 6 to 10 in 1985 by region, and gini of household income by region. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. For sample of 6-14 years old females, the reported pairs cluster bootstrap-t p-value is based on bootstrap replications with no missing Wald statistics. Statistically significant: *** 1% level, ** 5% level, * 10% level.

Table 1-10 The impact of remittances on child illiteracy (ages 6-14 years old)

		Males				Females			
		Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: coefficient estimates									
Remittances		-0.2203	-1.1168*	-0.7220	-0.1943	-0.1205	-1.7332***	-1.1546**	-0.9936
		(0.1282)	(0.5446)	(0.7551)	(0.1291)	(0.1178)	(0.5135)	(0.5629)	(0.6688)
		[0.1415]	[0.5697]	[0.7024]		[0.1239]	[0.3061]	[0.5457]	
Panel B: p-values based on different rejection methods									
N(0,1)		0.1195		0.3039	0.1322	0.3309		0.0343	0.1374
t(G-1)		0.1321	0.0612	0.3138		0.3402	6.818e-06	0.0444	
t(G-2)		0.1326	0.0616	0.3142		0.3406	7.891e-06	0.0449	
t(G-L)		0.1360	0.0648	0.3168		0.3431	18.58e-06	0.0477	
WRE bootstrap:									
Symmetric	Rademacher		0.2420				0.0168		
test	Mammen		0.2367				0.0175		
Equal-tailed	Rademacher		0.1930				0.0286		
test	Mammen		0.1000				0.0310		
Restricted score bootstrap:									
Symmetric	Rademacher	0.0746		0.4834		0.2866		0.3552	
test	Mammen	0.0849		0.4927		0.2946		0.3736	
Equal-tailed	Rademacher	0.0702		0.4870		0.2886		0.3666	
test	Mammen	0.0480		0.4610		0.3232		0.2748	
Pairs cluster bootstrap-t								0.1105	
Panel C: test statistics									
p-values of endogeneity tests:									
Woolridge's score test			0.0120				0.0004		
Wald test of ρ=0				0.4564				0.1179	
Instrument relevance:									
p-value of Wald test				0.000	0.001			0.000	0.000
Effective F statistic			24.40				30.93		
p-value- score test of normality				0.0000				0.0000	
Number of observations		25,426				24,164			

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: a dummy for the observation being the oldest child in the household, last finished schooling of the parent, dummies for marital status and age of the household head, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gross enrollment ratio of children aged 6 to 10 in 1985 by region, and gini of household income by region. Historical regional gross enrollment ratios are for historical male enrollment rates in columns 1-4, and historical female enrollment rates in columns 5-8. The dependent variable is a dummy taking value 1 if the child is illiterate and 0 otherwise. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26.

L is the number of exogenous regressors that are invariant within clusters and includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gross enrollment ratio of children aged 6 to 10 in 1985 by region, and gini of household income by region. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. For sample of 6-14 years old females, the reported pairs cluster bootstrap-t p-value is based on bootstrap replications with no missing Wald statistics. Statistically significant: *** 1% level, ** 5% level, * 10% level.

Table 1-11 The impact of remittances on school attendance of children aged 15 to 19

		Males				Females							
		Regressions including controls for labor market characteristics				Regressions including controls for labor market characteristics				Regressions omitting controls for labor market characteristics			
		Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: coefficient estimates													
Remittances		0.1490	-5.4538***	-0.2808	0.4172*	0.0929	-6.0528*	-1.0146*	-0.5869***	0.0954	-1.7054	-0.9799*	-0.8192***
		(0.0986)	(1.9451)	(0.6491)	(0.2505)	(0.0986)	(3.8597)	(0.3711)	(0.1994)	(0.0985)	(1.3360)	(0.4059)	(.2908)
		[0.1005]	[1.002]	[0.8723]		[0.0862]	[3.1199]	[0.5277]		[0.0856]	[1.1175]	[0.5436]	
Educational system reform		1.1545***	0.3797***	1.1527***	1.9655***	1.0479***	0.3093***	1.0355***	1.2398***	1.0482***	0.3262***	1.0364***	1.1885***
		[0.0489]	[0.0186]	[0.0495]	(0.2134)	[0.0581]	[0.0258]	[0.0593]	(0.0969)	[0.0581]	[0.0231]	[0.0586]	(0.1308)
Panel B: p-values based on different rejection methods													
N(0,1)		0.1382		0.7474	0.0959	0.2812		0.0545	0.0033	0.2651		0.0714	0.0048
t(G-1)		0.1507	0.000012	0.7501		0.2915	0.0637	0.0659		0.2757	0.1395	0.0835	
t(G-2)		0.1512	0.000013	0.7502		0.2919	0.0642	0.0664		0.2761	0.1400	0.0840	
t(G-L)		0.1604	0.000087	0.7521		0.2994	0.0727	0.0751		0.2790	0.1434	0.0873	
WRE bootstrap:													
Symmetric test	Rademacher		0.0283				0.1291				0.2427		
	Mammen		0.0241				0.0635				0.1714		
Equal-tailed test	Rademacher		0.0462				0.1402				0.2298		
	Mammen		0.0410				0.0198				0.0928		
Restricted score bootstrap:													
Symmetric test	Rademacher	0.1418		0.7707		0.3097		0.1835		0.2949		0.2166	
	Mammen	0.1380		0.7755		0.3137		0.1863		0.2967		0.2272	
Equal-tailed test	Rademacher	0.1412		0.7823		0.3078		0.1916		0.2902		0.2282	
	Mammen	0.1176		0.7085		0.2610		0.1378		0.2416		0.1722	
Pairs cluster bootstrap-t								0.6863				0.6323	
Panel C: test statistics													
p-values of endogeneity tests:													
Woolridge's score test			0.0000				0.0008				0.0891		
Wald test of ρ=0				0.6071				0.0652				0.0838	
Instrument relevance:													
p-value of Wald test				0.000	0.002			0.099	0.407			0.004	0.060
Effective F statistic			59.94				3.62				11.89		
p-value of Anderson-Rubin test							0.0235				0.1580		
p-value - score test of normality				0.0000				0.0000				0.0000	
Number of observations		14,677				14,478							

Notes: Models in columns 1-8 also include year fixed effects in addition to individual, household and region level covariates: a dummy for the observation being the oldest child in the household, last finished schooling of the parent, dummies for marital status and age of the household head, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Models in columns 9-12 include all the controls as in columns 5-8 except for controls that capture region level labor market characteristics: share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree, unemployment rate for males 15 years old or older, share of men aged 15-64 working in agricultural sector, and share of men aged 15-64 working in private sector. Net enrollment ratios calculated as averages over years 2003-2011 are for male net enrollment rates in columns 1-4, and female net enrollment rates in columns 5-12. The dependent variable is a dummy taking value 1 if the child attends school and 0 otherwise. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for columns 1-8 includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region; for columns 9-12 controls for regional labor market characteristics are excluded from L: share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Presented p-values with asymptotic refinement are for remittances. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 1,336 and 1,177 bootstrap replications for sample of girls in IV bivariate probit models with and without controls for labor market characteristics, respectively. Statistically significant: *** 1% level, ** 5% level, * 10% level.

Table 1-12 The impact of remittances on child labor (boys aged 15 to 19)

	Dependent variables															
	Any market work				Wage work				Unpaid family work				Self-employment			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																
Remittances	-0.2055	4.6267***	-0.0014	0.3734	-0.0045	2.2054***	-0.2564	0.0116	-0.5978***	2.6554**	-0.7417	-1.1907***	-0.1377	-0.2340	2.2267	1.8500**
	(0.1058)	(1.7317)	(0.6187)	(0.2828)	(0.1083)	(1.0303)	(0.5730)	(0.9012)	(0.1876)	(1.0538)	(1.9941)	(0.4405)	(0.3523)	(0.2121)	(1.7963)	(0.8579)
	[0.1325]	[1.3553]	[0.6283]		[0.1390]	[0.7533]	[0.6174]		[0.1597]	[0.9752]	[1.9285]		[0.3542]	[0.1288]	[1.3876]	
Educational system reform	-0.6140***	-0.1734***	-0.6136***	-0.9113***	-0.5553***	-0.1058***	-0.5553***	-1.1114***	-0.3642***	-0.0587***	-0.3644***	-0.5825***	-0.5982***	-0.0089***	-0.5943***	-0.9561***
	[0.0574]	[0.0171]	[0.0572]	(0.1188)	[0.0635]	[0.0153]	[0.0636]	(0.1836)	[0.0479]	[0.0130]	[0.0479]	(0.0931)	[0.1562]	[0.0026]	[0.1566]	(0.3687)
Panel B: p-values based on different rejection methods																
N(0,1)	0.1208		0.99820	0.1867	0.97388		0.6779	0.9896	0.0002		0.7005	0.0068	0.6974		0.1086	0.0310
t(G-1)	0.1333	0.0021	0.99821		0.97414	0.0071	0.6814		0.0009	0.0116	0.7037		0.7007	0.0813	0.1211	
t(G-2)	0.1338	0.0022	0.99822		0.97415	0.0073	0.6815		0.0010	0.0118	0.7039		0.7008	0.0817	0.1216	
t(G-L)	0.1430	0.0041	0.99823		0.97434	0.0110	0.6841		0.0021	0.0164	0.7063		0.7032	0.0907	0.1308	
WRE bootstrap:																
Symmetric Rademacher		0.0661				0.0605				0.1659				0.2914		
test Mammen		0.0695				0.0714				0.1575				0.2671		
Equal-tailed Rademacher		0.0808				0.0710				0.1978				0.2828		
test Mammen		0.0396				0.0706				0.1104				0.2578		
Restricted score bootstrap:																
Symmetric Rademacher	0.1430		n.a.		0.9755		0.6918		0.0000		0.7738		0.8492		0.4593	
test Mammen	0.1463		n.a.		0.9765		0.7047		0.0019		0.7806		0.7743		0.4647	
Equal-tailed Rademacher	0.1386		n.a.		0.9757		0.6889		0.0000		0.7657		0.8475		0.4614	
test Mammen	0.0870		n.a.		0.9709		0.6551		0.0000		0.7749		0.9889		0.2728	
Pairs cluster bootstrap-t																
Panel C: test statistics																
p-values of endogeneity tests:																
Woolridge's score test		0.0010				0.0051				0.0074				0.0782		
Wald test of ρ=0			0.7273				0.6594				0.9417				0.1485	
Instrument relevance:																
p-value of Wald test			0.000	0.005			0.000	0.006			0.000	0.016			0.000	0.064
Effective F statistic		59.94				59.94				59.94				59.94		
p-value - score test of normality			0.2534				0.0000				0.0000				0.0000	
Number of observations	14,677															

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: a dummy for the observation being the oldest child in the household, last finished schooling of the parent, dummies for marital status and age of the household head, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Net enrollment ratios calculated as averages over years 2003-2011 are for male net enrollment rates. The dependent variables are dummies capturing labor force participation decisions of boys: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of his own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Presented p-values with asymptotic refinement are for remittances. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in

IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-13 The impact of remittances on child labor (girls aged 15 to 19)

	Dependent variables															
	Any market work				Wage work				Unpaid family work				Self-employment			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																
Remittances	-0.3979***	-3.6078	0.2427	1.5211***	-0.6138***	-3.1119	-0.4110	-1.9613***	-0.1216	-0.2190	0.4677	0.4062	n.a.	-0.2769	n.a.	n.a.
	(0.1267)	(2.4285)	(0.9032)	(0.4958)	(0.1887)	(1.9315)	(0.7802)	(0.6974)	(0.1554)	(1.2018)	(1.6593)	(1.8877)		(0.2053)		
	[0.0788]	[4.4829]	[1.1659]		[0.1760]	[1.9208]	[0.8137]		[0.1350]	[2.7854]	[1.9025]			[0.1776]		
Educational system reform	-0.4413***	-0.1106***	-0.4387***	-0.7106***	-0.5608***	-0.0753***	-0.5600***	-1.1288***	-0.2333***	-0.0341**	-0.2312***	-0.2762***	n.a.	-0.0011	n.a.	n.a.
	[0.0685]	[0.0270]	[0.0704]	(0.1068)	[0.0715]	[0.0195]	[0.0718]	(0.1356)	[0.0670]	[0.0147]	[0.0692]	(0.1078)		[0.0018]		
Panel B: p-values based on different rejection methods																
N(0,1)	0.00000		0.8351	0.0022	0.0005		0.6134	0.0049	0.3678		0.8058	0.8296	n.a.		n.a.	n.a.
t(G-1)	0.00003	0.4285	0.8367		0.0018	0.1178	0.6178		0.3764	0.93795	0.8077		n.a.	0.1316	n.a.	
t(G-2)	0.00004	0.4288	0.8368		0.0019	0.1182	0.6180		0.3767	0.93797	0.8078		n.a.	0.1321	n.a.	
t(G-L)	0.00017	0.4343	0.8380		0.0036	0.1275	0.6213		0.3830	0.93844	0.8093		n.a.	0.1414	n.a.	
WRE bootstrap:																
Symmetric test Rademacher		0.4553				0.1779				0.9396				0.1792		
Symmetric test Mammen		0.4528				0.2010				0.9322				0.1900		
Equal-tailed test Rademacher		0.2833				0.0954				0.8831				0.0670		
Equal-tailed test Mammen		0.2427				0.0506				0.8566				0.0296		
Restricted score bootstrap:																
Symmetric test Rademacher	0.0002		0.8505		0.0002		0.6125		0.3373		0.8325		n.a.		n.a.	
Symmetric test Mammen	0.0023		0.8560		0.0022		0.6199		0.3500		0.8287		n.a.		n.a.	
Equal-tailed test Rademacher	0.0000		0.8557		0.0002		0.6013		0.3424		0.8395		n.a.		n.a.	
Equal-tailed test Mammen	0.0000		0.7627		0.0000		0.5757		0.3402		0.7263		n.a.		n.a.	
Pairs cluster bootstrap-t																
Panel C: test statistics																
p-values of endogeneity tests:																
Woolridge's score test		0.2856				0.0084				0.9405				0.0068		
Wald test of ρ=0			0.5804				0.7949				0.7526				n.a.	
Instrument relevance:																
p-value of Wald test			0.183	0.975			0.143	0.934			0.178	0.313			n.a.	n.a.
Effective F statistic		3.62				3.62				3.62				3.62		
p-value of Anderson-Rubin test		0.3445				0.0567				0.9363				0.0569		
p-value - score test of normality			0.0005				0.0004				0.0000					
Number of observations								14,478								

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: a dummy for the observation being the oldest child in the household, last finished schooling of the parent, dummies for marital status and age of the household head, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Net enrollment ratios calculated as averages over years 2003-2011 are for female net enrollment rates. The dependent variables are dummies capturing labor force participation decisions of girls: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of her own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Presented p-values with asymptotic refinement are for remittances. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-14 The impact of remittances on child labor (girls aged 15 to 19 – models omit controls for regional labor market characteristics)

	Dependent variables															
	Any market work				Wage work				Unpaid family work				Self-employment			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																
Remittances	-0.4144***	-5.8226	-1.4508**	-0.5525**	-0.6412***	-4.0809***	-1.7414**	-1.8335***	-0.1325	-1.5265	-0.8190	-0.2490**	n.a.	-0.2151***	n.a.	-6.6259***
	(0.1264)	(2.1477)	(0.5539)	(0.2262)	(0.1870)	(1.5085)	(0.6352)	(0.3650)	(0.1556)	(0.8342)	(0.5482)	(0.1046)		(0.1081)		(1.8773)
	[0.0843]	[3.2732]	[0.6144]		[0.1745]	[1.0141]	[0.8434]		[0.1459]	[2.5258]	[0.6548]			[0.0655]		
Educational system reform	-0.4391***	-0.1203***	-0.4394***	-1.0611***	-0.5523***	-0.0788***	-0.5470***	-0.9612***	-0.2386***	-0.0406***	-0.2410***	-0.1475***	n.a.	-0.0009	n.a.	-0.0841
	[0.0688]	[0.0282]	[0.0685]	(0.1228)	[0.0711]	[0.0204]	[0.0784]	(0.2946)	[0.0681]	[0.0146]	[0.0692]	(0.0457)		[0.0015]		(0.3812)
Panel B: p-values based on different rejection methods																
N(0,1)	0.00000		0.0182	0.0146	0.0002		0.0389	0.0000	0.3638		0.2110	0.0174	n.a.		n.a.	0.0004
t(G-1)	0.00004	0.0874	0.0263		0.0011	0.00046	0.0494		0.3725	0.5510	0.2226		n.a.	0.0030	n.a.	
t(G-2)	0.00005	0.0879	0.0266		0.0012	0.00049	0.0499		0.3728	0.5512	0.2231		n.a.	0.0031	n.a.	
t(G-L)	0.00009	0.0912	0.0290		0.0016	0.00072	0.0528		0.3752	0.5527	0.2262		n.a.	0.0039	n.a.	
WRE bootstrap:																
Symmetric Rademacher		0.2540				0.0391				0.6220				0.0136		
test Mammen		0.2809				0.0153				0.6230				0.0305		
Equal-tailed Rademacher		0.1632				0.0780				0.5873				0.0102		
test Mammen		0.0512				0.0224				0.5583				0.0218		
Restricted score bootstrap:																
Symmetric Rademacher	0.0000		0.3374		0.0001		0.3880		0.3345		0.4360		n.a.		n.a.	
test Mammen	0.0030		0.3366		0.0012		0.3643		0.3389		0.4432		n.a.		n.a.	
Equal-tailed Rademacher	0.0000		0.3290		0.0000		0.3792		0.3332		0.4276		n.a.		n.a.	
test Mammen	0.0000		0.3144		0.0000		0.2434		0.3416		0.4518		n.a.		n.a.	
Pairs cluster bootstrap-t			0.6203				0.6438									
Panel C: test statistics																
p-values of endogeneity tests:																
Woolridge's score test		0.0086				0.0000				0.4978				0.0020		
Wald test of ρ=0			0.1807				0.3778				0.3105				n.a.	
Instrument relevance:																
p-value of Wald test			0.000	0.142			0.016	0.223			0.001	0.179			n.a.	0.191
Effective F statistic		11.89				11.89				11.89				11.89		
p-value of Anderson-Rubin test		0.1305				0.0436				0.5419				0.0422		
p-value - score test of normality			0.0040				0.0003				0.0000				n.a.	
Number of observations	14,478															

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: a dummy for the observation being the oldest child in the household, last finished schooling of the parent, dummies for marital status and age of the household head, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, and gini of household income by region. Net enrollment ratios calculated as averages over years 2003-2011 are for female net enrollment rates. The dependent variables are dummies capturing labor force participation decisions of girls: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of her own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, net enrollment ratio of children aged 15 to 19 by region, and gini of household income by region. Presented p-values with asymptotic refinement are for remittances. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 1,170 and 1,155 bootstrap replications in IV bivariate probit models for any market work and wage work, respectively. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-15 The impact of remittances on adult labor (males aged 20 to 24)

		Dependent variables															
		Any market work				Wage work				Unpaid family work				Self-employment			
		Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																	
Remittances		-0.2785*	-0.0253	-1.4942**	-1.3859***	-0.1392	-1.0612	-1.0448	-1.4292***	-0.2797	1.1239	-1.8397***	-0.3795	-0.1180	-0.0880	-1.7352***	-1.1496***
		(0.1114)	(0.7102)	(0.5485)	(0.2696)	(0.1129)	(0.7317)	(0.6563)	(0.4191)	(0.1495)	(0.5572)	(0.3731)	(0.3068)	(0.1748)	(0.3438)	(0.3458)	(0.2996)
		[0.1566]	[0.6266]	[0.7459]		[0.1424]	[0.8010]	[0.8204]		[0.1463]	[0.6598]	[0.2813]		[0.1683]	[0.4687]	[0.3274]	
Panel B: p-values based on different rejection methods																	
N(0,1)		0.0753		0.0452	0.0000	0.3285		0.2028	0.0006	0.0559		6.165e-11	0.2160	0.4831		0.000000	0.0001
t(G-1)		0.0875	0.96806	0.0561		0.3378	0.1972	0.2145		0.0674	0.1009	7.518e-07		0.4895	0.85253	0.000017	
t(G-2)		0.0880	0.96807	0.0565		0.3382	0.1976	0.2150		0.0678	0.1014	9.180e-07		0.4898	0.85259	0.000019	
t(G-L)		0.0956	0.96827	0.0635		0.3439	0.2050	0.2222		0.0751	0.1091	9.363e-06		0.4938	0.85353	0.000089	
WRE bootstrap:																	
Symmetric	Rademacher		0.9751				0.3424				0.1608				0.9251		
test	Mammen		0.9735				0.3688				0.1720				0.8838		
Equal-tailed	Rademacher		0.9697				0.3446				0.1550				0.9339		
test	Mammen		0.9779				0.3158				0.0710				0.7775		
Restricted score bootstrap:																	
Symmetric	Rademacher	0.1349		0.2252		0.3759		0.2505		0.0328		n.a.		0.4576		n.a.	
test	Mammen	0.1387		0.2246		0.3873		0.2675		0.0410		n.a.		0.4716		n.a.	
Equal-tailed	Rademacher	0.1378		0.2244		0.3874		0.2468		0.0336		n.a.		0.4556		n.a.	
test	Mammen	0.0484		0.1608		0.3010		0.1798		0.0166		n.a.		0.4788		n.a.	
Pairs cluster bootstrap-t				0.1000								0.1565				0.1105	
Panel C: test statistics																	
p-values of endogeneity tests:																	
Woolridge's score test			0.9085				0.2004				0.0651				0.8697		
Wald test of ρ=0				0.1240				0.2802				0.0063				0.3205	
Instrument relevance:																	
p-value of Wald test				0.000	0.000			0.000	0.000			0.000	0.000			0.000	0.000
Effective F statistic			88.86				88.86				88.86				88.86		
p-value - score test of normality				0.0237				0.0058				0.0000				0.0039	
Number of observations									11,661								

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the individual being the household head, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing labor force participation decisions of males: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of his own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 5 bootstrap replications in IV bivariate probit models for any market work, unpaid family work and self-employment. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-16 The impact of remittances on adult labor (females aged 20 to 24)

		Dependent variables															
		Any market work				Wage work				Unpaid family work				Self-employment			
		Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																	
Remittances		-0.0476	0.3144	-0.8629	-1.5046***	-0.2181	-1.2025*	-1.2690**	-1.6032***	0.1427	1.4825**	0.2631	0.0502	0.0426	0.0345	-1.0619***	-0.8229***
		(0.0986)	(0.5314)	(0.6470)	(0.3765)	(0.1183)	(0.4445)	(0.4598)	(0.2388)	(0.1336)	(0.4753)	(0.7385)	(0.2583)	(0.2602)	(0.1245)	(0.2771)	(0.2906)
		[0.1281]	[0.9578]	[0.8504]		[0.1108]	[0.6115]	[0.5647]		[0.2245]	[0.5972]	[0.8127]		[0.2722]	[0.1582]	[0.3543]	
Panel B: p-values based on different rejection methods																	
N(0,1)		0.7097		0.3102	0.0001	0.0491		0.0246	0.0000	0.5250		0.7461	0.8457	0.8753		0.0027	0.0046
t(G-1)		0.7128	0.7454	0.3199		0.0602	0.0604	0.0337		0.5307	0.0201	0.7487		0.8766	0.82900	0.0060	
t(G-2)		0.7129	0.7455	0.3203		0.0607	0.0609	0.0341		0.5309	0.0204	0.7488		0.8767	0.82907	0.0062	
t(G-L)		0.7148	0.7471	0.3263		0.0678	0.0680	0.0401		0.5345	0.0253	0.7505		0.8774	0.83017	0.0090	
WRE bootstrap:																	
Symmetric	Rademacher		0.8490				0.1751				0.1042				0.9099		
test	Mammen		0.8200				0.1614				0.1194				0.8819		
Equal-tailed	Rademacher		0.8547				0.1282				0.1592				0.9051		
test	Mammen		0.6553				0.0400				0.1120				0.7751		
Restricted score bootstrap:																	
Symmetric	Rademacher	0.7120		0.2488		0.0614		0.0032		0.7242		0.7394		0.8816		0.1445	
test	Mammen	0.7302		0.2501		0.0719		0.0186		0.6897		0.7579		0.9049		0.1818	
Equal-tailed	Rademacher	0.7169		0.2428		0.0618		0.0030		0.7349		0.7439		0.8659		0.1460	
test	Mammen	0.7617		0.1970		0.0294		0.0002		0.5071		0.7017		0.8313		0.0460	
Pairs cluster bootstrap-t								0.1345								0.0760	
Panel C: test statistics																	
p-values of endogeneity tests:																	
Woolridge's score test			0.7459				0.0074				0.0570				0.8425		
Wald test of ρ=0				0.3631				0.1401				0.8944				0.0243	
Instrument relevance:																	
p-value of Wald test				0.000	0.000			0.000	0.000			0.000	0.000			0.000	0.000
Effective F statistic			10.18				10.18				10.18				10.18		
p-value of Anderson-Rubin test			0.7648				0.0422				0.1562				0.8359		
p-value - score test of normality				0.0000				0.0020				0.0005				0.0000	
Number of observations		15,630															

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the individual being the household head, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing labor force participation decisions of females: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of her own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region.

Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS

models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 5 bootstrap replications in IV bivariate probit models for wage work and self-employment. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-17 The impact of remittances on adult labor (males of ages 20-24 years old who currently live with their parents)

	Dependent variables															
	Any market work				Wage work				Unpaid family work				Self-employment			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																
Remittances	-0.2968*	-0.2592	-1.1219	-1.2656***	-0.1468	-1.0699	-0.5116	-0.7744	-0.2411	1.1172	-2.0189***	-2.0192**	-0.2193	-0.3065	-1.7260***	-0.7928**
	(0.1235)	(1.007)	(0.8420)	(0.4039)	(0.1248)	(1.0152)	(0.9102)	(0.5588)	(0.1562)	(0.7680)	(0.6814)	(1.0521)	(0.2201)	(0.4370)	(0.8420)	(0.3636)
	[0.1718]	[0.8595]	[1.0197]		[0.1599]	[1.0539]	[0.9977]		[0.1539]	[0.8115]	[0.5248]		[0.2165]	[0.5087]	[0.5081]	
Panel B: p-values based on different rejection methods																
N(0,1)	0.0840		0.2712	0.0017	0.3588		0.6081	0.166	0.1172		0.0001	0.0550	0.3111		0.0007	0.0292
t(G-1)	0.0963	0.7654	0.2817		0.3675	0.3197	0.6126		0.1298	0.1808	0.0007		0.3208	0.5523	0.0022	
t(G-2)	0.0968	0.7655	0.2821		0.3679	0.3201	0.6127		0.1303	0.1813	0.0008		0.3212	0.5524	0.0023	
t(G-L)	0.1045	0.7670	0.2885		0.3733	0.3261	0.6155		0.1380	0.1888	0.0015		0.3271	0.5558	0.0039	
WRE bootstrap:																
Symmetric Rademacher		0.8235				0.4621				0.2128				0.7102		
test Mammen		0.8196				0.5079				0.2192				0.6987		
Equal-tailed Rademacher		0.8257				0.4718				0.2118				0.7385		
test Mammen		0.8371				0.4522				0.1132				0.6113		
Restricted score bootstrap:																
Symmetric Rademacher	0.1483		0.3101		0.3950		0.6096		0.0799		n.a.		0.2530		n.a.	
test Mammen	0.1410		0.3283		0.4010		0.6218		0.0902		n.a.		0.2614		n.a.	
Equal-tailed Rademacher	0.1488		0.3100		0.4050		0.5997		0.0790		n.a.		0.2530		n.a.	
test Mammen	0.0654		0.3046		0.3500		0.6417		0.0634		n.a.		0.2732		n.a.	
Pairs cluster bootstrap-t											0.1490				0.6533	
Panel C: test statistics																
p-values of endogeneity tests:																
Woolridge's score test		0.8593				0.3304				0.1218				0.5970		
Wald test of ρ=0			0.4157				0.7039				0.3661				0.3722	
Instrument relevance:																
p-value of Wald test			0.000	0.000			0.000	0.000			0.000	0.015			0.000	0.048
Effective F statistic		29.61				29.61				29.61				29.61		
p-value - score test of normality			0.0124				0.0098				0.0000				0.0743	
Number of observations								9,875								

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing labor force participation decisions of males: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of his own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 9 and 1,064 bootstrap replications in IV bivariate probit models for unpaid family work and self-employment, respectively. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-18 The impact of remittances on adult labor (females of ages 20-24 years old who currently live with their parents)

		Dependent variables															
		Any market work				Wage work				Unpaid family work				Self-employment			
		Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																	
Remittances		0.0271	-0.4388	-0.6611	0.8011*	-0.1201	-0.9916	-1.0609	-0.1316	0.2663	0.3890	-0.0957	0.1091	n.a.	0.1637**	n.a.	-3.9593
		(0.1262)	(0.8871)	(0.7307)	(0.4780)	(0.1412)	(0.7862)	(0.7836)	(0.3376)	(0.1732)	(0.5626)	(1.0988)	(0.2703)		(0.1960)		(20.262)
		[0.1485]	[2.0862]	[0.8963]		[0.1300]	[1.0745]	[0.8138]		[0.2847]	[1.2288]	[1.4859]			[0.0689]		
Panel B: p-values based on different rejection methods																	
N(0,1)		0.8548		0.4607	0.0938	0.3554		0.1924	0.6966	0.3496		0.94861	0.6863	n.a.		n.a.	0.8451
t(G-1)		0.8563	0.8350	0.4676		0.3642	0.3649	0.2042		0.3585	0.7542	0.94912		n.a.	0.0255	n.a.	
t(G-2)		0.8564	0.8351	0.4679		0.3645	0.3652	0.2047		0.3589	0.7543	0.94914		n.a.	0.0258	n.a.	
t(G-L)		0.8572	0.8362	0.4721		0.3700	0.3706	0.2120		0.3644	0.7559	0.94946		n.a.	0.0312	n.a.	
WRE bootstrap:																	
Symmetric	Rademacher		0.8685				0.5003				0.8162				0.0544		
test	Mammen		0.8586				0.4568				0.8042				0.0511		
Equal-tailed	Rademacher		0.8587				0.4903				0.8381				0.0956		
test	Mammen		0.8609				0.3710				0.7519				0.0810		
Restricted score bootstrap:																	
Symmetric	Rademacher	0.8638		0.5026		0.3520		0.2475		0.6056		0.9636		n.a.		n.a.	
test	Mammen	0.8765		0.5190		0.3620		0.2800		0.5998		0.9604		n.a.		n.a.	
Equal-tailed	Rademacher	0.8777		0.5013		0.3522		0.2530		0.6203		0.9595		n.a.		n.a.	
test	Mammen	0.8111		0.4932		0.3346		0.1828		0.4118		0.8837		n.a.		n.a.	
Pairs cluster bootstrap-t																	
Panel C: test statistics																	
p-values of endogeneity tests:																	
Woolridge's score test			0.8204				0.2695				0.8021				0.0325		
Wald test of ρ=0				0.4371				0.3087				0.7915				n.a.	
Instrument relevance:																	
p-value of Wald test				0.001	0.000			0.001	0.005			0.004	0.002			n.a.	0.026
Effective F statistic			5.873				5.873				5.873				5.873		
p-value of Anderson-Rubin test			0.8228				0.2782				0.7734				0.1087		
p-value - score test of normality				0.8364				0.3905				0.1645				n.a.	
Number of observations		7,771															

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing labor force participation decisions of females: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of her own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-19 The impact of remittances on adult labor (males aged 25 to 49)

	Dependent variables															
	Any market work				Wage work				Unpaid family work				Self-employment			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																
Remittances	-0.4714***	-0.2930	1.3949***	-1.5072***	-0.2484***	-4.9887***	-1.6485***	-1.1425***	0.1170	1.6040***	1.3656***	0.4294**	-0.0744	3.0916***	1.1651***	0.2085*
	(0.0603)	(0.5704)	(0.2044)	(0.1516)	(0.0546)	(1.2575)	(0.2470)	(0.4135)	(0.1268)	(0.4091)	(0.4452)	(0.1768)	(0.0626)	(0.9529)	(0.3378)	(0.1203)
	[0.0718]	[0.7189]	[0.2337]		[0.0708]	[1.0126]	[0.2960]		[0.1113]	[0.3813]	[0.4621]		[0.0551]	[0.6470]	[0.2888]	
Panel B: p-values based on different rejection methods																
N(0,1)	5.213e-11		2.412e-09	0.0000	0.0005		0.000000	0.0057	0.2932		0.0031	0.0152	0.1765		0.0001	0.0831
t(G-1)	7.068e-07	0.6871	3.133e-06		0.0017	0.00004	0.000008		0.3032	0.0002	0.0067		0.1885	0.00006	0.0004	
t(G-2)	8.645e-07	0.6872	3.693e-06		0.0018	0.00005	0.000009		0.3037	0.0003	0.0069		0.1890	0.00007	0.0005	
t(G-L)	8.966e-06	0.6893	2.581e-05		0.0031	0.00018	0.000053		0.3098	0.0007	0.0098		0.1965	0.00024	0.0010	
WRE bootstrap:																
Symmetric Rademacher		0.8158				0.0515				0.0651				0.0160		
test Mammen		0.7797				0.0092				0.0273				0.0145		
Equal-tailed Rademacher		0.8155				0.1018				0.1258				0.0320		
test Mammen		0.6661				0.0170				0.0254				0.0286		
Restricted score bootstrap:																
Symmetric Rademacher	0.0001		n.a.		0.0059		0.0218		0.3616		0.2115		0.1809		0.0477	
test Mammen	0.0028		n.a.		0.0126		0.0305		0.3733		0.2232		0.1935		0.0670	
Equal-tailed Rademacher	0.0000		n.a.		0.0052		0.0214		0.3540		0.2118		0.1764		0.0478	
test Mammen	0.0000		n.a.		0.0002		0.0024		0.3006		0.1414		0.1174		0.0116	
Pairs cluster bootstrap-t			0.0160				0.0040				0.1300				0.0050	
Panel C: test statistics																
p-values of endogeneity tests:																
Woolridge's score test		0.7907				0.0000				0.0001				0.0086		
Wald test of ρ=0			0.0009				0.0001				0.0137				0.0002	
Instrument relevance:																
p-value of Wald test			0.001	0.000			0.000	0.000			0.000	0.000			0.000	0.000
Effective F statistic		15.28				15.28				15.28				15.28		
p-value of Anderson-Rubin test		0.6868				0.0437				0.0571				0.0444		
p-value - score test of normality			0.0237				0.0000				0.0000				0.0000	
Number of observations								63,991								

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the individual being the household head, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing labor force participation decisions of males: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of his own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region.

Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS

models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 5 bootstrap replications in IV bivariate probit models for any market work, wage work, unpaid family work and self-employment. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-20 The impact of remittances on adult labor (females aged 25 to 49)

	Dependent variables															
	Any market work				Wage work				Unpaid family work				Self-employment			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																
Remittances	-0.1084	1.0870	-1.0089***	-0.3253***	-0.1853	-1.6620**	-1.6159***	-0.7194***	0.0622	2.5050**	0.9873**	0.0274	-0.0648	0.2440	0.3293	0.9608***
	(0.0478)	(0.4426)	(0.2253)	(0.1236)	(0.0594)	(0.3508)	(0.1182)	(0.2474)	(0.0712)	(0.4748)	(0.3910)	(0.1024)	(0.0696)	(0.2111)	(0.3702)	(0.2957)
	[0.0679]	[2.2247]	[0.3100]		[0.1158]	[0.7600]	[0.1379]		[0.0940]	[0.9329]	[0.4768]		[0.0684]	[0.9442]	[0.4249]	
Panel B: p-values based on different rejection methods																
N(0,1)	0.1106		0.0011	0.0085	0.1098		0.0000	0.0036	0.5081		0.0384	0.7891	0.3433		0.4384	0.0012
t(G-1)	0.1231	0.6293	0.0032		0.1223	0.0383	1.198e-11		0.5141	0.0126	0.0488		0.3523	0.7981	0.4456	
t(G-2)	0.1236	0.6295	0.0033		0.1228	0.0387	2.048e-11		0.5144	0.0129	0.0493		0.3527	0.7982	0.4459	
t(G-L)	0.1314	0.6321	0.0053		0.1306	0.0450	5.992e-09		0.5181	0.0169	0.0560		0.3583	0.7995	0.4503	
WRE bootstrap:																
Symmetric test Rademacher		0.9275				0.0853				0.2142				0.8429		
Symmetric test Mammen		0.8463				0.0902				0.1809				0.8201		
Equal-tailed test Rademacher		0.9287				0.1120				0.2960				0.8495		
Equal-tailed test Mammen		0.5391				0.0712				0.1822				0.7339		
Restricted score bootstrap:																
Symmetric test Rademacher	0.1213		0.0443		0.0959		0.0004		0.5653		0.3295		0.3496		0.5089	
Symmetric test Mammen	0.1276		0.0484		0.0777		0.0093		0.5648		0.3677		0.3515		0.5146	
Equal-tailed test Rademacher	0.1170		0.0438		0.0906		0.0006		0.5713		0.3414		0.3494		0.5021	
Equal-tailed test Mammen	0.1038		0.0094		0.0778		0.0000		0.4798		0.2296		0.3490		0.5019	
Pairs cluster bootstrap-t			0.0140				0.0025				0.1300					
Panel C: test statistics																
p-values of endogeneity tests:																
Woolridge's score test		0.6379				0.0179				0.0373				0.7989		
Wald test of ρ=0			0.0094				0.0000				0.0506				0.3197	
Instrument relevance:																
p-value of Wald test			0.000	0.000			0.000	0.000			0.000	0.000			0.000	0.000
Effective F statistic		15.92				15.92				15.92				15.92		
p-value of Anderson-Rubin test		0.6697				0.0057				0.1780				0.8027		
p-value - score test of normality			0.0000				0.0000				0.0000				0.0000	
Number of observations	68,862															

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the individual being the household head, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing labor force participation decisions of females: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of her own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region.

Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS

models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 5 bootstrap replications in IV bivariate probit models for any market work, wage work, and unpaid family work. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-21 The impact of remittances on adult labor (males aged 50 to 64)

	Dependent variables															
	Any market work				Wage work				Unpaid family work				Self-employment			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																
Remittances	-0.4913***	-1.3484	1.2388***	1.1356***	-0.2237***	-2.9835**	-0.6899	-0.2706	-0.3410	0.1552	-1.6830*	-0.1719	-0.4005***	1.4798	1.1802***	0.1559
	(0.0731)	(0.7779)	(0.2223)	(0.0936)	(0.0899)	(0.8832)	(0.8475)	(10.308)	(0.3045)	(0.1234)	(0.6278)	(0.2578)	(0.0813)	(0.7492)	(0.2834)	(0.1873)
	[0.0797]	[1.7049]	[0.3085]		[0.0676]	[1.1259]	[1.2554]		[0.2763]	[0.1066]	[0.9611]		[0.1091]	[1.1612]	[0.4361]	
Panel B: p-values based on different rejection methods																
N(0,1)	7.385e-10		0.0001	0.0000	0.0009		0.5826	0.9791	0.2172		0.0799	0.5050	0.0002		0.0068	0.4052
t(G-1)	1.942e-06	0.4364	0.0004		0.0028	0.0137	0.5875		0.2287	0.1578	0.0922		0.0011	0.2142	0.0120	
t(G-2)	2.316e-06	0.4367	0.0005		0.0029	0.0140	0.5877		0.2291	0.1583	0.0927		0.0012	0.2147	0.0123	
t(G-L)	1.833e-05	0.4413	0.0011		0.0047	0.0181	0.5907		0.2362	0.1659	0.1003		0.0022	0.2219	0.0162	
WRE bootstrap:																
Symmetric Rademacher		0.7001				0.1986				0.2998				0.5024		
test Mammen		0.6508				0.2398				0.3180				0.4628		
Equal-tailed Rademacher		0.6579				0.2422				0.3534				0.5869		
test Mammen		0.4892				0.0166				0.3184				0.4238		
Restricted score bootstrap:																
Symmetric Rademacher	0.0001		n.a.		0.0009		0.6682		0.1011		n.a.		0.0008		n.a.	
test Mammen	0.0028		n.a.		0.0081		0.7043		0.0782		n.a.		0.0095		n.a.	
Equal-tailed Rademacher	0.0002		n.a.		0.0010		0.6667		0.1014		n.a.		0.0010		n.a.	
test Mammen	0.0000		n.a.		0.0000		0.6137		0.0798		n.a.		0.0002		n.a.	
Pairs cluster bootstrap-t			0.1170								0.7328				0.0925	
Panel C: test statistics																
p-values of endogeneity tests:																
Woolridge's score test		0.3981				0.0001				0.1642				0.3009		
Wald test of ρ=0			0.0000				0.7205				0.5632				0.0022	
Instrument relevance:																
p-value of Wald test			0.000	0.000			0.001	0.560			0.000	0.000			0.000	0.000
Effective F statistic		8.87				8.87				8.87				8.87		
p-value of Anderson-Rubin test		0.3617				0.0737				0.3015				0.3752		
p-value - score test of normality			0.0000				0.0052				0.0000				0.0000	
Number of observations								24,185								

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the individual being the household head, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing labor force participation decisions of males: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of his own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region.

Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS

models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 5 bootstrap replications in IV bivariate probit models for any market work and self-employment; for nonwage labor the corresponding figure is 928. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-22 The impact of remittances on adult labor (females aged 50 to 64)

	Dependent variables															
	Any market work				Wage work				Unpaid family work				Self-employment			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																
Remittances	-0.1005	0.0248	-0.4343	0.0139	0.0696	-0.3713**	-1.4672***	-1.4800**	-0.2242**	0.3497	-0.4290	0.3679	0.0446	0.0464	1.0437	0.0806
	(0.0752)	(0.3340)	(0.3827)	(0.1328)	(0.1071)	(0.1305)	(0.1861)	(0.7484)	(0.0959)	(0.2912)	(0.8562)	(0.4990)	(0.1057)	(0.1667)	(0.6536)	(0.1571)
	[0.0884]	[2.0461]	[0.7056]		[0.1486]	[0.1444]	[0.2220]		[0.1056]	[1.3486]	[1.6202]		[0.1074]	[0.6908]	[0.6591]	
Panel B: p-values based on different rejection methods																
N(0,1)	0.2554		0.5382	0.9163	0.6394		3.876e-11	0.0480	0.0338		0.7912	0.4609	0.6775		0.1132	0.6081
t(G-1)	0.2661	0.99040	0.5437		0.6434	0.0165	6.343e-07		0.0438	0.7974	0.7933		0.6810	0.94696	0.1258	
t(G-2)	0.2666	0.99041	0.5439		0.6435	0.0167	7.780e-07		0.0442	0.7975	0.7934		0.6811	0.94699	0.1263	
t(G-L)	0.2732	0.99047	0.5474		0.6460	0.0213	8.310e-06		0.0508	0.7988	0.7947		0.6833	0.94732	0.1341	
WRE bootstrap:																
Symmetric test Rademacher		0.9959				0.0835				0.9581				0.9646		
Symmetric test Mammen		0.9941				0.0754				0.8995				0.9602		
Equal-tailed test Rademacher		0.9979				0.1380				0.9601				0.9737		
Equal-tailed test Mammen		0.7133				0.0884				0.5795				0.8459		
Restricted score bootstrap:																
Symmetric test Rademacher	0.2669		0.6564		0.6965		n.a.		0.0272		n.a.		0.6926		0.5210	
Symmetric test Mammen	0.2771		0.6484		0.7022		n.a.		0.0305		n.a.		0.6993		0.5365	
Equal-tailed test Rademacher	0.2612		0.6585		0.6981		n.a.		0.0268		n.a.		0.7001		0.5215	
Equal-tailed test Mammen	0.2330		0.7693		0.6039		n.a.		0.0102		n.a.		0.6761		0.4366	
Pairs cluster bootstrap-t							0.0030									
Panel C: test statistics																
p-values of endogeneity tests:																
Woolridge's score test		0.9804				0.0102				0.7834				0.9535		
Wald test of ρ=0			0.6380				0.0150				0.8993				0.1419	
Instrument relevance:																
p-value of Wald test			0.000	0.000			0.000	0.006			0.000	0.000			0.000	0.003
Effective F statistic		14.16				14.16				14.16				14.16		
p-value of Anderson-Rubin test		0.9903				0.0565				0.8097				0.9469		
p-value - score test of normality			0.0000				0.0037				0.0000				0.0000	
Number of observations									24,116							

Notes: All models also include year fixed effects in addition to individual, household and region level covariates: last finished schooling of the individual, a dummy for the individual being the household head, a dummy for the marital status of the individual, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females (including the individual in consideration), dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing labor force participation decisions of females: working for wage, working as unpaid family worker, being self-employed, and participating in any market work; and they stand for: having a regular job in return of a salary or working as a seasonal or temporary worker in exchange of a wage; working in a household enterprise without getting paid; doing a job of her own either by employing someone for a wage or employing unpaid family workers; and being employed in any of the aforementioned market work. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region.

Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS

models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 5 bootstrap replications in IV bivariate probit model for wage work. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-23 The impact of remittances on household well-being – part 1

		Dependent variables															
		40 % of the median of the per adult equivalent yearly household disposable income				50 % of the median of the per adult equivalent yearly household disposable income				60 % of the median of the per adult equivalent yearly household disposable income				70 % of the median of the per adult equivalent yearly household disposable income			
		Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: coefficient estimates																	
Remittances		-0.2188***	-4.5523***	-1.3584***	-0.2133	-0.2708***	-3.5131**	-0.0285	-0.2197	-0.2116***	-1.7288	0.0452	-0.3277*	-0.1991***	-0.3229	0.2875	0.1590
		(0.0554)	(0.5467)	(0.2120)	(0.2408)	(0.0490)	(0.4652)	(0.3825)	(0.1578)	(0.0440)	(0.3451)	(0.3171)	(0.1729)	(0.0415)	(0.3024)	(0.1893)	(0.7681)
		[0.0651]	[1.1770]	[0.3154]		[0.0571]	[1.3045]	[0.6687]		[0.0485]	[1.3942]	[0.4908]		[0.0476]	[1.6080]	[0.2904]	
Panel B: p-values based on different rejection methods																	
N(0,1)		0.0008		0.00001	0.3758	0.00000		0.9659	0.164	0.0000		0.92648	0.0581	0.00002		0.3222	0.207
t(G-1)		0.0024	0.0006	0.00022		0.00007	0.0124	0.9662		0.0001	0.2265	0.92721		0.00031	0.8424	0.3316	
t(G-2)		0.0025	0.0007	0.00024		0.00008	0.0127	0.9663		0.0002	0.2269	0.92724		0.00033	0.8425	0.3320	
t(G-L)		0.0042	0.0015	0.00062		0.00026	0.0166	0.9664		0.0005	0.2340	0.92770		0.00080	0.8435	0.3378	
WRE bootstrap:																	
Symmetric	Rademacher		0.0749				0.1906				0.6487				0.9775		
test	Mammen		0.0699				0.1866				0.5833				0.9348		
Equal-tailed	Rademacher		0.1360				0.2496				0.6559				0.9757		
test	Mammen		0.0384				0.1584				0.4282				0.5759		
Restricted score bootstrap:																	
Symmetric	Rademacher	0.0076		0.2020		0.0005		0.9793		0.0025		0.9469		0.0015		0.5090	
test	Mammen	0.0249		0.2237		0.0059		0.9788		0.0097		0.9503		0.0077		0.4954	
Equal-tailed	Rademacher	0.0068		0.1996		0.0002		0.9837		0.0018		0.9397		0.0012		0.5121	
test	Mammen	0.0002		0.0902		0.0000		0.7541		0.0000		0.8783		0.0000		0.5313	
Pairs cluster bootstrap-t				0.1725													
Panel C: test statistics																	
p-values of endogeneity tests:																	
Woolridge's score test			0.0025				0.0321				0.2882				0.8690		
Wald test of ρ=0				0.0111				0.7121				0.5937				0.1000	
Instrument relevance:																	
p-value of Wald test				0.000	0.000			0.000	0.000			0.000	0.000			0.000	0.000
Effective F statistic			16.00				16.00				16.00				16.00		
p-value of Anderson-Rubin test			0.0847				0.1506				0.3668				0.8489		
p-value - score test of normality				0.0000				0.0000				0.0000				0.0000	
Number of observations		98,557															

Notes: All models also include year fixed effects in addition to household and region level covariates: a dummy for having a married household head, dummies for the age of the household head, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing household well-being taking values 1 if the household is located below 40%, 50%, 60% or 70% of the median of the per adult equivalent yearly household disposable income distribution, and taking values 0 otherwise. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models.

Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 5 bootstrap replications in column 3. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-24 The impact of remittances on household well-being – part 2

	Dependent variables											
	50 % of the median of the per adult equivalent monthly household expenditure				Daily per adult equivalent expenditure levels of 2.15$				Daily per adult equivalent expenditure levels of 4.30$			
	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP	Probit	IV 2SLS	IV bivariate probit	SNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: coefficient estimates												
Remittances	-0.1986***	-2.4261**	0.3693*	0.4249	-0.2223	-0.1624**	-1.2145***	-0.4871	-0.2250***	-1.3889***	-0.1338	-0.3239
	(0.0505)	(0.3791)	(0.1674)	(0.3511)	(0.2442)	(0.0562)	(0.4000)	(0.5686)	(0.0968)	(0.2279)	(0.2722)	(0.4065)
	[0.0458]	[1.0037]	[0.1932]		[0.2385]	[0.0621]	[0.2841]		[0.0713]	[0.3595]	[0.3783]	
Panel B: p-values based on different rejection methods												
N(0,1)	0.00001		0.0560	0.226	0.3511		0.00001	0.3916	0.0016		0.7235	0.4256
t(G-1)	0.00020	0.0232	0.0675		0.3600	0.0149	0.00024		0.0041	0.00070	0.7265	
t(G-2)	0.00022	0.0236	0.0680		0.3604	0.0152	0.00026		0.0043	0.00074	0.7266	
t(G-L)	0.00059	0.0288	0.0752		0.3658	0.0195	0.00066		0.0065	0.00153	0.7284	
WRE bootstrap:												
Symmetric Rademacher		0.2855				0.0788				0.0481		
test Mammen		0.2536				0.0550				0.0378		
Equal-tailed Rademacher		0.3132				0.1050				0.0736		
test Mammen		0.1976				0.0434				0.0206		
Restricted score bootstrap:												
Symmetric Rademacher	0.0016		0.1849		0.2689		0.1404		0.0008		0.7272	
test Mammen	0.0099		0.1714		0.2533		0.2408		0.0054		0.7380	
Equal-tailed Rademacher	0.0010		0.1858		0.2682		0.1400		0.0006		0.7305	
test Mammen	0.0000		0.1674		0.3008		0.0388		0.0000		0.6709	
Pairs cluster bootstrap-t			0.0275				0.0490					
Panel C: test statistics												
p-values of endogeneity tests:												
Woolridge's score test		0.0326				0.0016				0.0001		
Wald test of ρ=0			0.0045				0.0286				0.8088	
Instrument relevance:												
p-value of Wald test			0.000	0.000			0.000	0.000			0.000	0.000
Effective F statistic		16.00				16.00				16.00		
p-value of Anderson-Rubin test		0.1584				0.0433				0.0496		
p-value - score test of normality			0.0000				0.0000				0.0000	
Number of observations	98,557											

Notes: All models also include year fixed effects in addition to household and region level covariates: a dummy for having a married household head, dummies for the age of the household head, the highest schooling level attained by a member of the household, number of 0-5 years old children, number of 6-19 years old male and female children, number of 20-64 years old adult males and females, dummies for ownership of piped water and natural gas systems, dummy for rural residence, regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. The dependent variables are dummies capturing household well-being taking values 1 if the household is located below 50% of the median of the per adult equivalent monthly household expenditure distribution, and daily per adult equivalent expenditure levels are less than 2.15$ and 4.30$, and taking values 0 otherwise. The instrument is regional migration rate in 1985. Heteroskedasticity robust standard errors are in parenthesis. Cluster robust standard errors are in brackets. Wald tests are based on cluster robust standard errors. The number of clusters (G) is 26. L is the number of exogenous regressors that are invariant within clusters and for all models includes: regional development index in 1973, length of road per 1 km^2 in 1980 by region, share of asphalt roads in 1985 by region, interaction of length and share of roads by region, number of schools per 1,000 children aged 6 to 16 in 1985 by region, gini of household income by region, share of men between 25 and 64 years old with high school degree and the corresponding share for men with above high school degree by region, unemployment rate for males 15 years old or older by region, share of men aged 15-64 working in agricultural sector by region, and share of men aged 15-64 working in private sector by region. Small sample modifications have been applied to account for the downward bias in standard errors due to having few clusters. Small sample modifications include inflating cluster robust standard error estimates by a factor of $\sqrt{\frac{G}{G-1}}$ in probit and IV bivariate probit regressions; and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ in IV 2SLS regressions where N is the number of observations and k is the number of regressors. Stata reports p-values based on t(G-1) distribution with "ivregress" command for IV 2SLS models with small sample modifications. Stata uses standard normal distribution as basis for p-value calculations in probit, IV bivariate probit and SNP models. Wild restricted efficient residual and restricted score bootstraps use 9,999; pairs cluster bootstrap-t uses 1,999 bootstrap replications. In calculating p-values by pairs cluster bootstrap-t, one or more parameters could not be estimated in 5 bootstrap replications in columns 3 and 7. Statistically significant: *** 1% level, ** 5% level, * 10% level. n.a. stands for not applicable.

Table 1-25 Treatment effects of receiving remittances on outcomes

		Treatment Effects			
		LATE	ATE (AME)		
<u>Outcomes:</u>	*# of observations*	IV 2SLS	Probit	IV bivariate probit	SNP
Attendance of 6-14-years-old boys (Table 1-9)	25,426	0.9714 (0.6608)	0.0259 (0.0159)	0.0572 (0.0579)	0.0238*** (0.0085)
Attendance of 6-14-years-old girls (Table 1-9)	24,164	2.5102*** (0.4970)	0.0263 (0.0167)	0.1106*** (0.0280)	0.0322* (0.0167)
Illiteracy of 6-14-years-old boys (Table 1-10)	25,426	-1.1168* (0.5697)	-0.0246* (0.0133)	-0.0572** (0.0288)	-0.0212** (0.0105)
Illiteracy of 6-14-years-old girls (Table 1-10)	24,164	-1.7332*** (0.3061)	-0.0159 (0.0150)	-0.0789*** (0.0124)	-0.0656*** (0.0071)
Attendance of 15-19-years-old boys (regressions controlling for labor market characteristics- Table 1-11)	14,677	-5.4538*** (1.002)	0.1490 (0.1005)	-0.0966 (0.3003)	0.0829* (0.0490)
Attendance of 15-19-years-old girls (regressions controlling for labor market characteristics- Table 1-11)	14,478	-6.0528* (3.1199)	0.0299 (0.0276)	-0.2920** (0.1204)	-0.1510*** (0.0501)
Attendance of 15-19-years-old girls (regressions omitting labor market controls- Table 1-11)	14,478	-1.7054 (1.1175)	0.0307 (0.0274)	-0.2841** (0.1267)	-0.2098*** (0.0626)
Child labor- boys aged 15 to 19 (Table 1-12)					
Any market work	14,677	4.6267*** (1.3553)	-0.0603 (0.0368)	-0.0004 (0.1939)	0.0692 (0.0504)
Wage work	14,677	2.2054*** (0.7533)	-0.0011 (0.0337)	-0.0562 (0.1203)	0.0013 (0.1066)
Unpaid family work	14,677	2.6554** (0.9752)	-0.0648*** (0.0112)	-0.0743 (0.1148)	-0.0701*** (0.0150)
Self-employment	14,677	-0.2340 (0.1288)	-0.0020 (0.0045)	0.3334 (0.4629)	0.0134 (0.0105)
Child labor- girls aged 15 to 19 (Table 1-13)					
Any market work	14,478	-3.6078 (4.4829)	-0.0748*** (0.0121)	0.0592 (0.3091)	0.1985*** (0.0304)
Wage work	14,478	-3.1119 (1.9208)	-0.0575*** (0.0096)	-0.0439 (0.0636)	-0.0688*** (0.0098)
Unpaid family work	14,478	-0.2190 (2.7854)	-0.0134 (0.0139)	0.0669 (0.3242)	0.0432 (0.2463)
Self-employment	14,478	-0.2769 (0.1776)	n.a.	n.a.	n.a.
Child labor- girls aged 15 to 19 (Table 1-14) (regressions omitting labor market controls)					
Any market work	14,478	-5.8226 (3.2732)	-0.0782*** (0.0131)	-0.1663*** (0.0245)	-0.0527*** (0.0177)
Wage work	14,478	-4.0809*** (1.0141)	-0.0593*** (0.0098)	-0.0876*** (0.0109)	-0.0707*** (0.0046)
Unpaid family work	14,478	-1.5265 (2.5258)	-0.0148 (0.0151)	-0.0654** (0.0301)	-0.0167*** (0.0065)
Self-employment	14,478	-0.2151*** (0.0655)	n.a.	n.a.	-0.0017*** (0.0003)

Table 1-25 (continued)

Adult labor- males aged 20 to 24 (Table 1-15)						
	Any market work	11,661	-0.0253 (0.6266)	-0.0953* (0.0544)	-0.4586*** (0.1576)	-0.3425*** (0.0509)
	Wage work	11,661	-1.0612 (0.8010)	-0.0484 (0.0487)	-0.2968* (0.1589)	-0.2329*** (0.0468)
	Unpaid family work	11,661	1.1239 (0.6598)	-0.0441** (0.0199)	-0.1423*** (0.0059)	-0.0523 (0.0355)
	Self-employment	11,661	-0.0880 (0.4687)	-0.0107 (0.0140)	-0.0611*** (0.0083)	-0.0367*** (0.0052)
Adult labor- females aged 20 to 24 (Table 1-16)						
	Any market work	15,630	0.3144 (0.9578)	-0.0140 (0.0373)	-0.1946 (0.1272)	-0.1780*** (0.0319)
	Wage work	15,630	-1.2025* (0.6115)	-0.0420** (0.0192)	-0.1531*** (0.0287)	-0.1330*** (0.0122)
	Unpaid family work	15,630	1.4825** (0.5972)	0.0195 (0.0327)	0.0377 (0.1288)	0.0050 (0.0262)
	Self-employment	15,630	0.0345 (0.1582)	0.0010 (0.0069)	-0.0106*** (0.0022)	-0.0068*** (0.0012)
Adult labor- males aged 20-24 who live with their parents (Table 1-17)						
	Any market work	9,875	-0.2592 (0.8595)	-0.1053* (0.0615)	-0.3732 (0.2737)	-0.2458*** (0.0684)
	Wage work	9,875	-1.0699 (1.0539)	-0.0513 (0.0547)	-0.1664 (0.2851)	-0.1612** (0.0767)
	Unpaid family work	9,875	1.1172 (0.8115)	-0.0415* (0.0233)	-0.1556*** (0.0097)	-0.1352*** (0.0221)
	Self-employment	9,875	-0.3065 (0.5087)	-0.0159 (0.0128)	-0.0495*** (0.0094)	-0.0216*** (0.0066)
Adult labor- females aged 20-24 who live with their parents (Table 1-18)						
	Any market work	7,771	-0.4388 (2.0862)	0.0095 (0.0523)	-0.1983 (0.2149)	0.1534 (0.1052)
	Wage work	7,771	-0.9916 (1.0745)	-0.0332 (0.0346)	-0.2067** (0.0872)	-0.0205 (0.0500)
	Unpaid family work	7,771	0.3890 (1.2288)	0.0388 (0.0462)	-0.0118 (0.1766)	0.0107 (0.0274)
	Self-employment	7,771	0.1637** (0.0689)	n.a.	n.a.	-0.0059*** (0.0021)
Adult labor- males aged 25 to 49 (Table 1-19)						
	Any market work	63,991	-0.2930 (0.7189)	-0.1024*** (0.0192)	0.1070*** (0.0055)	-0.2320*** (0.0218)
	Wage work	63,991	-4.9887*** (1.0126)	-0.0896*** (0.0261)	-0.5042*** (0.0496)	-0.2718*** (0.0681)
	Unpaid family work	63,991	1.6040*** (0.3813)	0.0045 (0.0045)	0.0978* (0.0551)	0.0216** (0.0105)
	Self-employment	63,991	3.0916*** (0.6470)	-0.0216 (0.0155)	0.4043*** (0.0965)	0.0451* (0.0270)

Table 1-25 (continued)

Adult labor- females aged 25 to 49 (Table 1-20)					
Any market work	68,862	1.0870 (2.2247)	-0.0313* (0.0190)	-0.2196*** (0.0439)	-0.0622*** (0.0203)
Wage work	68,862	-1.6620** (0.7600)	-0.0309* (0.0174)	-0.1410*** (0.0048)	-0.0855*** (0.0134)
Unpaid family work	68,862	2.5050** (0.9329)	0.0086 (0.0135)	0.1901 (0.1175)	0.0033 (0.0126)
Self-employment	68,862	0.2440 (0.9442)	-0.0055 (0.0055)	0.0376 (0.0596)	0.1607* (0.0891)
Adult labor- males aged 50 to 64 (Table 1-21)					
Any market work	24,185	-1.3484 (1.7049)	-0.1770*** (0.0277)	0.3413*** (0.0506)	0.2598*** (0.0203)
Wage work	24,185	-2.9835** (1.1259)	-0.0574*** (0.0155)	-0.1441 (0.1770)	-0.0311 (1.1559)
Unpaid family work	24,185	0.1552 (0.1066)	-0.0043* (0.0024)	-0.0105** (0.0052)	-0.0021 (0.0028)
Self-employment	24,185	1.4798 (1.1612)	-0.1145*** (0.0282)	0.3889*** (0.1282)	0.0310 (0.0386)
Adult labor- females aged 50 to 64 (Table 1-22)					
Any market work	24,116	0.0248 (2.0461)	-0.0243 (0.0206)	-0.0941 (0.1298)	0.0022 (0.0212)
Wage work	24,116	-0.3713** (0.1444)	0.0054 (0.0123)	-0.0465*** (0.0057)	-0.0331*** (0.0049)
Unpaid family work	24,116	0.3497 (1.3486)	-0.0344** (0.0150)	-0.0611 (0.1951)	0.0715 (0.1024)
Self-employment	24,116	0.0464 (0.6908)	0.0036 (0.0091)	0.1698 (0.1712)	0.0061 (0.0129)
Household well-being- part1 (Table 1-23)					
40 % of the median of the per adult equivalent yearly household disposable income	98,557	-4.5523*** (1.1770)	-0.0267*** (0.0071)	-0.0999*** (0.0116)	-0.0230 (0.0233)
50 % of the median of the per adult equivalent yearly household disposable income	98,557	-3.5131** (1.3045)	-0.0438*** (0.0082)	-0.0050 (0.1169)	-0.0348 (0.0231)
60 % of the median of the per adult equivalent yearly household disposable income	98,557	-1.7288 (1.3942)	-0.0431*** (0.0092)	0.0098 (0.1085)	-0.0570** (0.0275)
70 % of the median of the per adult equivalent yearly household disposable income	98,557	-0.3229 (1.6080)	-0.0471*** (0.0105)	0.0742 (0.0781)	0.0352 (0.0286)
Household well-being- part2 (Table 1-24)					
50 % of the median of the per adult equivalent monthly household expenditure	98,557	-2.4261** (1.0037)	-0.0306*** (0.0066)	0.0693* (0.0405)	0.0744 (0.0632)
Daily per adult equivalent expenditure levels of 2.15$	98,557	-0.1624** (0.0621)	-0.0011 (0.0009)	-0.0028*** (0.0003)	-0.0016 (0.0012)
Daily per adult equivalent expenditure levels of 4.30$	98,557	-1.3889*** (0.3595)	-0.0098*** (0.0026)	-0.0061 (0.0160)	-0.0104 (0.0107)

Notes: IV 2SLS recovers estimates of LATE of remittances while the remaining nonlinear models recover estimates of ATE (AME) of remittances. Stata's "margins" command is implemented to estimate the average change in the probability of success with respect to a change in the remittance variable from 0 to 1. The estimates from nonlinear models are also known as average marginal effects of remittances. Standard errors are in parenthesis. Standard errors of treatment effect estimates for nonlinear models are calculated through delta method which uses the robust/clustered variance estimates of the original model parameters. For IV 2SLS, clustered robust standard errors are reported. p-value calculations are based on t(G-1) distribution for IV 2SLS and standard normal distribution for nonlinear models. * p<0.10, ** p<0.05, *** p<0.01. n.a. stands for not applicable.

Appendix

Table A1 Reduced form regressions for non-receiving samples

		Wald test of being in a historically high migration region on outcomes (p-value)	
	# of observations	OLS	Probit
Outcomes:			
Attendance of 6-14-years-old boys (Table 1-9)	25,113	0.679	0.664
Attendance of 6-14-years-old girls (Table 1-9)	23,879	0.208	0.126
Illiteracy of 6-14-years-old boys (Table 1-10)	25,113	0.626	0.739
Illiteracy of 6-14-years-old girls (Table 1-10)	23,879	0.605	0.546
Attendance of 15-19-years-old boys (regressions controlling for labor market characteristics- Table 1-11)	14,481	0.160	0.153
Attendance of 15-19-years-old girls (regressions controlling for labor market characteristics- Table 1-11)	14,286	0.259	0.197
Attendance of 15-19-years-old girls (regressions omitting labor market controls- Table 1-11)	14,286	0.042	0.038
Child labor- boys aged 15 to 19 (Table 1-12)			
Any market work	14,481	0.959	0.828
Wage work	14,481	0.162	0.200
Unpaid family work	14,481	0.433	0.369
Self-employment	14,481	0.042	0.091
Child labor- girls aged 15 to 19 (Table 1-13)			
Any market work	14,286	0.000	0.000
Wage work	14,286	0.076	0.242
Unpaid family work	14,286	0.000	0.000
Self-employment	14,286	0.198	0.108
Child labor- girls aged 15 to 19 (Table 1-14) (regressions omitting labor market controls)			
Any market work	14,286	0.000	0.000
Wage work	14,286	0.000	0.001
Unpaid family work	14,286	0.001	0.000
Self-employment	14,286	0.188	0.101
Adult labor- males aged 20 to 24 (Table 1-15)			
Any market work	11,518	0.404	0.440
Wage work	11,518	0.515	0.551
Unpaid family work	11,518	0.071	0.018
Self-employment	11,518	0.464	0.446
Adult labor- females aged 20 to 24 (Table 1-16)			
Any market work	15,428	0.123	0.160
Wage work	15,428	0.876	0.849
Unpaid family work	15,428	0.168	0.168
Self-employment	15,428	0.472	0.482
Adult labor- males aged 20-24 who live with their parents (Table 1-17)			
Any market work	9,758	0.151	0.159
Wage work	9,758	0.823	0.871
Unpaid family work	9,758	0.108	0.029
Self-employment	9,758	0.222	0.304

Table A1 (continued)

Adult labor- females aged 20-24 who live with their parents (Table 1-18)				
	Any market work	7,660	0.565	0.528
	Wage work	7,660	0.229	0.263
	Unpaid family work	7,660	0.108	0.140
	Self-employment	7,660	0.480	0.570
Adult labor- males aged 25 to 49 (Table 1-19)				
	Any market work	63,438	0.168	0.250
	Wage work	63,438	0.826	0.883
	Unpaid family work	63,438	0.408	0.563
	Self-employment	63,438	0.961	0.848
Adult labor- females aged 25 to 49 (Table 1-20)				
	Any market work	67,929	0.267	0.250
	Wage work	67,929	0.036	0.012
	Unpaid family work	67,929	0.224	0.169
	Self-employment	67,929	0.352	0.241
Adult labor- males aged 50 to 64 (Table 1-21)				
	Any market work	23,867	0.001	0.002
	Wage work	23,867	0.203	0.241
	Unpaid family work	23,867	0.993	0.693
	Self-employment	23,867	0.023	0.015
Adult labor- females aged 50 to 64 (Table 1-22)				
	Any market work	23,649	0.162	0.145
	Wage work	23,649	0.629	0.662
	Unpaid family work	23,649	0.062	0.044
	Self-employment	23,649	0.635	0.575
Household well-being- part1 (Table 1-23)				
	40 % of the median of the per adult equivalent yearly household disposable income	97,029	0.174	0.050
	50 % of the median of the per adult equivalent yearly household disposable income	97,029	0.184	0.121
	60 % of the median of the per adult equivalent yearly household disposable income	97,029	0.155	0.170
	70 % of the median of the per adult equivalent yearly household disposable income	97,029	0.231	0.268
Household well-being- part2 (Table 1-24)				
	50 % of the median of the per adult equivalent monthly household expenditure	97,029	0.110	0.059
	Daily per adult equivalent expenditure levels of 2.15$	97,029	0.487	n.a.
	Daily per adult equivalent expenditure levels of 4.30$	97,029	0.433	0.075

Notes: The results in this Table are outcomes of an indirect test for the exogeneity of the instrument. We split regions into two with respect to the cutoff - the median of the historical migration rate distribution. Then we estimate reduced form equations of outcomes on a dummy taking value 1 if the observation belongs to a historically high migration region —region that is above the median migration rate in 1985—for non-receiving samples. The reduced form equations include all the control variables from the corresponding structural equations omitting the dummy for receiving remittances. Wald tests take into account the clustered structure of the observations in OLS and probit models. p-value for Wald test of being in a historically high migration region is presented. p-value calculations employ small sample corrections: (i) inflate standard errors by a factor of $\sqrt{\frac{G}{G-1}}$ for probit models and by a factor of $\sqrt{\frac{G}{G-1}\frac{N-1}{N-k}}$ for OLS models, and (ii) use t(G-1) critical values instead of standard normal critical values for OLS models. n.a. stands for not applicable.

2 THE IMPACT OF MIGRANT NETWORKS ON IMMIGRANTS' LOCATION CHOICES

2.1 Introduction

Migrant networks, which are formed by the former migrants from a household or a community, lowers the costs and increases the net benefits of migration for potential migrants by means of providing information to the potential migrant about housing and labor markets at destination, providing direct assistance in terms of facilitating and funding the travel, and providing food, shelter and job referrals upon migrant's arrival,. For the reasons cited the positive network externalities are assumed to affect a household's decision to send migrants. McKenzie and Rapoport (2007) in the case of migration from rural Mexico to US, find that larger shares of migrants in a community is associated with an increase in the probability of a compatriot to migrate. This positive impact is more pronounced for the individuals in the lower end of the wealth distribution if migration networks are substantially large.

A perfect example in the Turkish context for the impact of migrant networks on migration propensities for the residents is from a county of Giresun known as Yağlıdere, located in Eastern Black Sea region. With the population exchange agreement signed between Turkey and Greece on 30.01.1923, residents of some parts of Eastern Black Sea region had to relocate to Greece. Parents of one of the families lost their lives while migrating from Yağlıdere to Greece, and their orphan named Lefter was raised by a family residing in Yağlıdere. Lefter, soon decided to look for his relatives and migrated first to Greece and from there to US. Long years later, he came back to Yağlıdere to visit the family that raised him; however, his foster mother was deceased already. Lefter noticed the poverty in the county and decided not to leave alone from his town. He took one person with him to the US in 1969 and the migration stream from Yağlıdere to US began with this one specific incidence. Until 1985, the migration stream from Yağlıdere continued with 2 to 3 persons per year. After 1985, there was a boom in the annual counts of migrants to the US from Yağlıdere. Nowadays, the population of Yağlıdere is around 16,000 and the immigrants in US who are born in Yağlıdere is more than 20,000 [76] ("ABD'nin Vize Engelini", 2017, para. 1-7).

[76] I thank Aziz Şerif Şimşir for bringing up this example to my attention.

Some studies focus on the externalities that migration networks present with respect to the employment outcomes of recent immigrants. Yamauchi and Tanabe (2008), concentrating on the Bangkok labor market, show that migration network has a negative impact on the employment probability of new immigrants while the impact of previous migrants' efficiency is in the opposite direction. In Yamauchi and Tanabe (2008) the migration network is measured as the relative share of the previous migrants from a particular province in the population of immigrants in Bangkok while the efficiency of previous migrants is a variable which captures the estimated employment probabilities of previous migrants by their origin provinces. The previous migrants and the recent migrants are substitutes in Bangkok labor market and as the network gets larger, new immigrants may need to compete with the previous migrants for the available jobs. The negative substitution effect is dominated by the positive scale effect as the efficiency of previous migrants is improved. Munshi (2003) investigates the network impacts on Mexican immigrants' employment prospects in the US conditional on the arrival of Mexican immigrants. Making use of data from *Mexican Migration Project*, he was able to utilize the variation in network variable over time which is defined as the proportion of migrants in a community who are in the US for any given year. He finds that migration network has positive effects on the employment probability and on the likelihood of having a nonagricultural job for a recent immigrant. He also points out that the established migrants who have arrived in the US four or more years earlier than the recent immigrants provide most of the job referrals and the support.

If migrant networks provide information and direct assistance to potential migrants, then it is reasonable to expect that the positive network externalities arise in destination locations where the migrant network is highly concentrated as network members are likely to provide more accurate information about locations they have settled in relative to other migration destinations (Davis et al., 2002). Establishing the role of migrant networks in enhancing migration from a source location is, however, compliacted due to potential confoundres. Most of the studies on economic impacts of migration rely on cross-sectional data which provides limited capability to control for the historical development of migration networks. The strong positive associations between migration networks and migration decisions of current households may actually be driven by factors that induced migration from a source location in the past and continue to influence migration from the same location in the present. Considering that households which reside in the same source location have much in common, and not all attributes of the migration decisions are observable by the econometrician, it is possible that some of the unobserved attributes correlate the past and current migration streams from a source location. While researchers mostly control for individual, household and source location specific characteristics to account for this possibility (see McKenzie and Rapoport, 2011; Binzel and Assaad, 2011), there is still room for a spurious positive relation between migrant networks and migration decisions. If it can be shown that location choices of former and latter migrants are related after accounting for differences in locational attributes across alternative locations then it supports the view that migrant networks, through providing information and assistance to potential migrants, affect the migration decisions of households.

Munshi (2003) states that while 28% of Mexican migrants from Michoacan settle in San Francisco, this share never exceeds 8% for the rest of the states in Mexico. In addition, 27% of Mexican migrants from Jalisco live in san Diego, yet this share is around 1% for migrants from San Luis Potosi. Bauer et al. (2007) adds to the descriptive statistics by showing that 58% of migrants from Guanajuato, the Mexican state with the highest emigration rate to the US, go to California and another 23% to Texas. In the Turkish context, Istanbul is the largest city in terms of both in- and out-migration in all census years between 1980 and 2000, where migration is defined as the change in the province of residence in the last 5 years (Kocaman, 2008). The cities with the lowest net migration counts—the difference between the numbers of immigrants to and emigrants from a province—between 1995 and 2000 are Samsun, Şanlıurfa, Diyarbakır, Erzurum, and Zonguldak, and the relative shares of their emigrants in Istanbul are respectively 34%, 9.9%, 17.7%, 23,9%, and 37.8% (Kocaman, 2008). The share of emigrants from Samsun during 1975-1980 period who choose to settle in Istanbul is 32.7%, and it constitutes the highest share of respective emigrant flows across all provinces in Turkey between 1975-1980 (Tandoğan, 1990). 20 years later, Istanbul is still the most favorable destination for the emigrants from Samsun. Sivas was among top 3 provinces with respect to the lowest net migration counts between 1975-1980, 1980-1985, and 1985-1990; and Sivas born migrants in Istanbul constitute around 4% of the population of Istanbul in 1975, 1980, 1985, 1990, and 2000. Sivas was also the leading province in Turkey with respect to the foreign-born population shares of Istanbul in these years (Kocaman, 2008; Murat et al. 1997; Başel, 2003). These observational evidence suggest that both past and current migrants are not uniformly distributed across destination locations.

The existing explanation for the clustering of immigrants in certain locations is the beneficial network externalities (see Gottlieb, 1987; Grossman, 1989; Marks, 1989; Chiswick and Miller, 1996; Zahniser, 1999; Munshi, 2003). Bartel (1989) shows that international migrants to the US from 1964 to 1980 choose to locate in standard metropolitan statistical areas (SMSAs) with high concentrations of their ethnic groups; though, more educated immigrants rely less on the ethnic enclaves and are more dispersed across the country compared to less educated immigrants. By modeling the preferences of immigrants over alternative SMSAs using conditional logit, she showed that labor market characteristics of destination such as average wage levels and unemployment rates are important determinants of location choice; although, unemployment rates are only statistically significant for immigrants of Hispanic origin. Foreign-born men are more likely to reside in SMSAs with higher average wages and higher average monthly general assistance payments, and for men of Hispanic origin higher unemployment rates are a deterrent. The most important determinant of the location choice is the share of the ethnic group in the US that resides in a SMSA. Distance has a negative and significant impact on the location decision of immigrants. Distance by proxying the travel, psychic and information gathering costs of a destination predicts that immigrants tend to live in SMSAs that are closer to their origin country. This issue has attracted lots of attention after the seminal work of Bartel (1989). Dunlevy (1991) studied the settlement patterns of Latin and Caribbean born immigrants from 11 different nations to the US who received legal permanent residence status in 1987. He found that migrant stocks for each nationality play an important role in the immigrants' destination location decisions. Zavodny (1999) investigates the locational choices of international migrants to US who are new recipients of legal permanent status and are new refugees between 1989 and 1994. He found a positive relationship between the flow of immigrants to states and the foreign-born share of state population for all new legal permanent residents and new refugees. Employment based legal permanent residents seem to be more sensitive to economic conditions of the locations: they prefer to live in states with higher manufacturing wage levels and lower unemployment. The difference between states with respect to welfare generosity seems to affect only refugees' locational choices; as expected, they choose to settle in states where they can enjoy higher welfare benefits. Davis et al. (2002), by making use of a data set where they observe immigrants from rural Mexico locating either in different states in US or in different states in Mexico, try to estimate the determinants of their location choices separately. They found that both for international and internal migrants, the share of total migrants from an ejido—a classification of agricultural land that is operated by small or medium sized producers in Mexico—in a given location has a positive and significant impact on the location choice of a migrant. Family level migrant networks also influence the settlement patterns of both international and internal migrants in the same way as ejido level networks do. Davis et al. (2002) found that family level and ejido level migrant networks are substitutes; that is, as the size of the ejido level network increases in a location, an additional migrant from the family settled in the same location is less influential on the location choice of a migrant. This implies that as the ejido level network size increases, the private information available for a family becomes more and more common knowledge within the ejido.

Bauer et al. (2007) examines the destination choices of Mexican migrants to US among 43 distinct locations. They allow for the migrant stock variables to have a nonlinear relationship with the probability of a migrant residing in a given location. Besides, they let migrants to follow the herd; that is, they allow for migrants to discount the information they receive from the migrant stocks and move to the locations that recent immigrants had gone with the presumption that the information that recent immigrants have is more valuable than the information that the migrant stocks provides. They include two migrant stock variables and one flow variable. The first stock variable is the fraction of the population of a US location that is constituted by Mexicans. The other stock variable measures the migration experience of a Mexican village in a US location relative to its migration experience in the whole US. The first stock measure captures the extent of ethnic goods available in a given US location while the second stock variable captures the extent of information available for a potential migrant in a Mexican village about a US location. The flow measure is calculated as the change in the village migration experience in a US location during the year preceding a potential migrant's location choice decision. They found that both stock variables have inverted U shape impacts on the probability of choosing a US location. As the size of the migrant stocks increase in a location, the positive network externalities improve prospective migrants' chances to move to that location with a decreasing rate. At a certain point, an additional increase in the stock causes negative network externalities to dominate; as the number of similar immigrants increase in a location, competition for available jobs would be inevitable considering that immigrants from the same source are substitutes of each other. After the turning point is reached, adding to the stock of migrants in a location decreases the propensities of migrants to migrate to that location. The flow impact, though, is positive on the location choice of a migrant. Immigrants are inclined to move to locations which attract relatively higher recent flows. Bauer et al. (2005) considers Mexican immigrants' location choices in US as a function of their English language proficiency and concludes that immigrants with low language abilities choose to migrate to locations with high Mexican shares of their respective populations. Their finding for the impact of the migrant stock on location choice is similar to their result in Bauer et al. (2007) where they find that the stock of migrants in a US location has an inverse U-shaped effect on a migrant's probability to choose that location.

Jaeger (2000) examines the intended location choices of male immigrants aged 21-54 when they entered the US during the fiscal year 1991 (October 1990-September 1991). He allows the demographic and economic factors of the location to have varying influences on locational propensities of male immigrants based on their admission category (visa status). He found that immigrants in all admission categories are highly responsive to the share of the population of US metropolitan area from immigrant's region of birth. Surprisingly, this effect is largest for the employment based immigrants. Local labor market characteristics such as expected wages and unemployment rates are more influential on employment based immigrant's chances to migrate to a metropolitan area. Despite the ties that family reunification based immigrants have with the stock of migrants in US, diversity immigrants constitute a random sample from the population of foreign-born individuals, conditional on applying to the lottery. Unemployment rate of a location has a negative and significant effect on the probability that the diversity based immigrant migrate to that location; however, the size of the effect is half of the corresponding figure for employment based immigrants. The impact of region of birth share in the population of a location on the probability of a diversity immigrant migrating to that location is on par with the corresponding impact on employment based immigrants. Jaeger in his 2007 study expands the estimation sample in his earlier work and looks at the intended settlement choices of newly arrived 25-to-60-years-old immigrants who entered US legally between 1971 and 2000. The methodological approach in his latter study differs from his former one basically in two ways: in the latter one, he allows for the network variables to have nonlinear impacts on location propensities of immigrants, and he accounts for the time constant heterogeneity in state characteristics by including state level fixed effects. His findings are similar to what he has found before. Region of birth concentration in the state population, which is measured as the share of the state population that comes from the immigrant's region of birth, is still found to be the most important network variable that affects an immigrant's (irrespective of his visa status) location choice. Labor market characteristics play an important role in migrants' destination choice where employment based immigrants form the most sensitive group to variations in wage levels and unemployment rates across alternative locations.

In addition to the studies on location choices of immigrants to US there are a number of other studies that focus on other host countries. Aslund (2005) investigates the location choices of immigrants to Sweden and their secondary migration destinations within the country. He found that the number of individuals from the immigrant's country of birth is a significant pull factor for both initial and subsequent location choice. Aslund (2005) found a smaller impact of overall immigrant density compared to an immigrant's country of birth concentration in a location. In addition, locations with high wages and low unemployment rates attract immigrants. There is little evidence in the study that immigrants are sensitive to variations in welfare generosity across locations. Damm (2009) focuses on secondary migration movements of immigrants within Denmark and tries to estimate the regional factors that push immigrants out of their initial locations. She showed that a small ethnic enclave, lack of housing and lack of institutions for qualifying education are the most important push factors. Immigrants respond to high levels of unemployment by moving out of the location as well. Findings of Aslund (2005) and Damm (2009) on European countries agree with US findings with respect to the responses of immigrants to concentrations of earlier settled immigrants of same origin and economic conditions of a location.

Fafchamps and Shilpi (2013) investigate the determinants of destination choice of internal migrants in the developing country context of Nepal. They contribute to the literature by studying internal migrants' preferences over locations which does not attract as much attention as international migrants' choices of migration destinations, and by providing evidence on determinants of migrants' location choice from a developing country. They find that migrants value high concentrations of individuals with similar ethnic and linguistic backgrounds in a location. Distance to place of origin is negatively correlated with the propensity to choose a location. Better access to amenities prove to be a pull factor for immigrants. Findings of Fafchamps and Shilpi (2013) compare to previous studies on migrants' location choices, and suggest that the impacts of destination attributes on the choice do not differ significantly between internal and international migration, as well in developed and developing country contexts.

Clustering of immigrants in a few locations is most likely to result in concentration of the economic and fiscal impacts of migration in these areas (Damm, 2009). Quantifying the effects of location characteristics on migration destination choice may help local administrators and policy makers to predict future waves of migration to locations and take precautions to provide the forthcoming immigrants with necessary services and infrastructure facilities. The legislators may benefit from the valuable information in preparing legislations which help in distributing new waves of migrants across the whole country, especially if sizable extent of clustering is shown to be detrimental for natives' as well as immigrants' welfare.

This study contributes to the scarce literature of determinants of internal migrants' destination choices by examining the locational factors that influence internal migrants' preferences over alternative provinces within the developing country context of Turkey by using data from two rounds of population censuses: 1990 and 2000. To the best of our knowledge, this is the first study conducted on this topic in Turkey. The study aims to provide evidence that helps to paint a clearer picture on internal migrants' responses to location attributes when deciding where to live.

2.2 Methodology

We try to estimate the impact of pull factors of locations on internal migrants' location propensities based on a discrete choice model. We closely follow the methodology applied in Jaeger (2007), and Fafchamps and Shilpi (2013). We model the utility that an internal migrant i from source province o gets from choosing province j as follows:

$$U_{ij} = \alpha L_{oj} + \beta X_{ioj} + \gamma_j Z_j + \varepsilon_{ij} \quad , \quad j = 1, 2, \dots, J \qquad (1)$$

where the stochastic utility function is linear in parameters and there are J possible destinations in a migrant's choice set. The coefficients α and β are fixed across choices and across individuals. L_{oj} is a vector of destination characteristics that varies by the source (origin) province of migrant, and X_{ioj} is a vector of interactions between destination province and individual characteristics that also varies by the source province of the migrant. Z_j controls for unobserved differences between provinces and the coefficients on province fixed effects γ_j varies over alternatives j. The reason for having the subscript o in the right-hand side terms is that the location attributes of a destination differ across origin provinces. For example, migrants evaluate the distance between the source and the destination while deciding on the location choice as higher distance is associated with higher transportation and psychic costs. Consider two potential migrants, one from source Ankara and one from Hakkari. If we assume that distance deters migration, then the coefficient on distance has negative sign, and the utility that the migrant from Ankara gets from migrating to Istanbul will be higher compared to the utility that the migrant from Hakkari gets in Istanbul, holding everything else constant. Since the distance to a destination differs across origins, the utility of the destination varies by the origin province of migrants. In other words, the attribute of a destination will be viewed differently by migrants from different source provinces. Our preferred specification involves evaluation of utilities in alternative destinations relative to the origin province by the potential migrant. That is, migrants compare location attributes of possible destinations with those characteristics in their origin provinces, and decide on the location choice based on this comparison. The implementation of this approach will be explained in detail but briefly we subtract the measure of the location attribute in origin from the location attribute in destination. The decision makers are utility maximizers; in other words, they compare the utilities they get from each alternative and choose the one with the highest utility[77]. If ε_{ij} follows type I extreme value distribution, and is independent and identically distributed over alternatives j, then the model parameters can be estimated by using McFadden's (1984) conditional logit model. Let y_{ij} be a random variable that takes the value 1 if individual i chooses province j, and takes value 0 otherwise. Then the probability of migrant i from origin o choosing province j is shown to be:

$$P(y_{ij} = 1) = \frac{\exp(\alpha L_{oj} + \beta X_{ioj})}{\sum_{k=1}^{J} \exp(\alpha L_{ok} + \beta X_{iok})} \tag{2}$$

Equation (2) gives the likelihood function for an individual i being observed in province j. After taking the logarithmic transformation of equation (2) and summing across all individuals $i = 1, 2, \ldots, N$, we can estimate model parameters α and β by maximum likelihood estimation strategy. The marginal effect of a change in a location's characteristic z_j—we intentionally drop the subscripts i and o—on the probability of a migrant choosing that location over others is calculated by taking the derivative of equation (2) with respect to z_j:

$$\frac{\partial P(y_{ij} = 1)}{\partial z_j} = [P(y_{ij} = 1)(1 - P(y_{ij} = 1)]\alpha_z \tag{3}$$

where α_z corresponds to the coefficient of location characteristic z in equation (1). Equation (3) implies that the marginal effect of a covariate varies with location j. If there is more uncertainty regarding the destination choice; that is, the choice probability $P(y_{ij} = 1)$ is close to 0.5, then a small change in the location's attribute induces more migrants to choose that province over others and the marginal effect is largest. However, if there is less uncertainty with regard to choosing a location—the choice probability $P(y_{ij} = 1)$ is close to either 0 or 1—, then a small change in the location's attribute does not contribute to a significant change in the share of immigrants choosing province j over others which interprets as a small marginal effect. In our case, the share of migrants in each location is different which implies that location probabilities $P(y_{ij} = 1)$ are different. As a result, the marginal effect of a change in a location attribute depends on the location. Therefore, we follow Jaeger (2007) in defining average marginal effect of a change in covariate z_j on $P(y_{ij} = 1)$ as

$$\frac{\partial \hat{P}(y_{ij} = 1)}{\partial z_j} = [\frac{1}{J}(1 - \frac{1}{J})]\hat{\alpha}_z \tag{4}$$

[77] Decision maker i chooses destination j if and only if $U_{ij} > U_{ik}\ \forall\ k \neq j$.

$\frac{1}{J}$ is the average probability of location assuming that immigrants are equally likely to live in any given province. In our study, we model the preferences of internal migrants over alternative destinations conditional on migrating as Fafchamps and Shilpi (2013) suggests. This implies that each migrant is observed in only one location, and this location is different than his province of origin[78]. The sample contains 67 provinces which covers the whole country. Thus, each migrant has a choice set with 66 destination alternatives and migrants from different source provinces have different choice sets. By multiplying the conditional logit estimates with $\left[\frac{1}{J}\left(1-\frac{1}{J}\right)\right] = \frac{1}{66}\left(1-\frac{1}{66}\right) \cong 0.0149$, we will be able to interpret the resulting product as the average effect of a change in a province's attribute on the probability of a migrant deciding to live in that province. We do not include non-migrants in our sample because mainly non-migrants and migrants differ in both their observed and unobserved characteristics, and the heterogeneity in individual traits, unless properly controlled, may bias the estimates of determinants of location choice. Although the heterogeneity caused by observable attributes can be controlled for in a conditional logit framework, unobserved differences between the two groups may create serious problems. For example, it is possible to think of a scenario where unobserved characteristics of non-migrants—like having relatives they cannot leave behind or having businesses they have in place of origin that they cannot afford to shut down—keep them in their place of origin. This suggests that the cost of migration is too high for non-migrants. If we include non-migrants in the analysis, then the variable which accounts for the migration costs in the location choice equation captures the impact of non-migrants' unobserved "stay" factors. Including individual-specific province-of-origin fixed effects[79] accounts for the unobserved heterogeneity in migration costs; however, individual-specific province-of-origin fixed effects would entirely account for non-migrants' decisions to stay at origin and including non-migrants and origin provinces as alternatives to the analysis of location choice, then, would provide no additional information (Fafchamps and Shilpi, 2009). In short, there may be many factors that determine the decision to migrate and to not conflate those with the determinants of migration destination choice, plus to minimize the bias that results from self-selection into migration, we drop non-migrants from the sample. On the other hand, some researchers argue that excluding non-migrants and hence source locations as alternatives may result in sample

[78] To clarify, province of origin refers to the location of the internal migrant 5 years prior to the survey date. Place of birth or province of birth corresponds to the immigrant's birth location.

[79] This variable takes value one if the destination is the province of the individual five years prior to the survey date and takes value zero otherwise. This variable compares to the "non-migration dummy" variable implemented in Davies et al. (2001). Non-migration dummy of Davies et al. (2001) differs from place-of-origin fixed effect by assigning value zero to migrants.

selection issues (see Davies et al., 2001; Sorensen et al., 2007) since the composition of the migrant subsample may be different from that of non-migrants, e.g. non-migrants under the possibility of migrating may respond differently to location attributes than the observed migrants in the sample react. To check for the sensitivity of our conditional logit estimates from the migrant sample, we estimate equation (2) for a combined sample of migrants and stayers in which origin provinces are treated as potential destination choices. We do not have information on international migrants; so, we study the determinants of location choices of internal migrants only.

It is impossible to observe the utility levels that immigrants would get in different locations. Thus, we need to think of the factors that determine an immigrant's utility from living in a location. Previous research (Bartel, 1989; Davies et al., 2001; Jaeger, 2000; Jaeger, 2007; Bauer et al., 2007) shows that immigrants respond to variations in economic conditions of locations. To capture differences in labor market conditions researchers generally include in their specifications average wage levels (or per capita income) and unemployment rates of locations (see Davies et al., 2001; Bauer et al., 2005; Jaeger, 2007). Turkish census data does not provide information on individuals' incomes, instead reports their occupation in the week before the survey and their last finished schooling level. Omitting average wage levels of locations would most likely result in endogeneity bias; as, the difference in income levels between locations is supposedly a key determinant that draws migrants together to a location both in the past and in the present. Bauer et al. (2007) and Bartel (1989) control for a location's population size and unemployment rate to capture the level of economic activity, level of labor demand and job opportunities in a location. Bauer et al. (2007) argues that controlling for unemployment rates also account for unobserved autocorrelated shocks to local labor markets which may drive migrants to locations which former migrants of the same origin do or do not consider as best alternatives. In other words, by including unemployment rates one achieves to control for the impact of unobserved local labor market attributes on migrants' location propensities. Another way to control for income differences between alternatives is to use a method as in Jaeger (2007) by estimating expected wage levels of immigrants in each alternative location. For that, firstly we need to have a random sample of the population in years 1985 and 1995 where we observe individuals' wages, their schooling attainment, and province of residence. Then for each skill level in each province we can get the average wage level. Lastly, for each internal migrant in each skill group who migrates in our sample between 1985-1990 or 1995-2000, we assign the corresponding figures from 1985 or 1995 as his expected wage levels in different provinces. However, we do not know of a data set as distant in past as

1985 which contains information on wage, schooling, and settlement of individuals. Therefore, we follow Bauer et al. (2007) in using a location's population size and unemployment rate as proxies for income level and economic conditions of a location. In an alternative specification, we replace population size with population density to control for the effect of a destination's job opportunities and economic conditions on migrant's utility.

As local labor market conditions are of interest for migrants who pursue better job opportunities and higher welfare by migrating, we restrict our sample to 28-54-years-old male internal migrants who are neither students nor retirees and are supposed to have a connection to the labor market[80]. Internal migration in our context is defined as the change in the province of residence in the past 5 years. The age restriction on the lower bound is, therefore, to ensure that migration is not due to pursuing schooling beyond high school level. In Turkey, schooling starts at age 6 and until one finishes university education 15 or 16 years elapse[81]. By age 23 most of the high academic achievers are supposed to exit the schooling phase of their lives. The law on pensions in Turkey allowed males to retire as young as 43 years of age until 08.09.1999 (Kızılot, 2012, para. 2). After that date, the retirement age is gradually increased. Since the census data comes from 1990 and 2000 for internal migrants, to make sure that migration due to retirement is not a concern the upper cap of the age restriction could be set at 42; then, however, the sample size would be reduced significantly. To capture migration destination preferences of prime-age males, we set the upper bound of the age restriction to be 54 and dropped the observations which state their reason for not working in the last week as being retired. Since the sample consists of males aged 28-54, provincial unemployment rates are calculated for 28-54-years-old males including both natives and immigrants. Agricultural sector in Turkey is large in the sense that the share of agricultural sector in total employment is 34% in 1985 and 29% in 1990. Hence, the average unemployment rates may not be good predictors of job availability in destinations. To counteract this problem, we test with two alternative measures of job opportunities in a destination: nonagricultural employment rate which is the share of total employment in a destination that is from nonagricultural sector, and

[80] We exclude military personnel from the estimation sample—to the extent that it is possible—since their location choice may be exogenous to economic and demographic conditions of locations and may be completely determined by the will of Turkish armed forces. Civil servants constitute another group that may not freely choose among the alternative destinations. Their location choices may be restricted to a subsample of the alternatives, and the desire of the corporation they work for may be an important determinant of their choice. Hence, estimation sample excludes civil servants as well.

[81] Assuming that the individual does not repeat grades and attain university as soon as he graduates from high school. Total length of schooling until the end of university depends on whether an individual attended a regular/vocational/religious vocational high school or Anatolian/science high school. The latter group includes an additional one year of preparatory grade.

nonagricultural unemployment rate which is the unemployment rate (in a destination) in the nonagricultural sector.

The identification strategy requires us to observe the location characteristics before migrants actually decide on migration destination to abstract from simultaneity issues. Large inflows of immigrants to a location may affect province level characteristics like unemployment rate and ease of access to amenities. If the researcher observes the location attributes after the migration flows have occurred, he mistakenly might conclude to a wrong direction of causation. The internal migrants in our sample are those who changed their province of residence between 1985-1990 or 1995-2000. Hence, the location characteristics are dated 1985 for the earlier flows and 1990 for the later flows. We gather information on location characteristics from 1985 census for internal migrants observed in 1990 census and had changed their province of residence between 1985 and 1990. Similarly, location attributes are derived from 1990 census for internal migrants observed in 2000 census and had left their province of origin between 1995 and 2000. We take 1990 locational characteristics as approximations to their 1995 counterparts; although, some attributes might have changed during the five-year period between 1990 and 1995. This is the best we can achieve as there is no reliable data set that presents demographic, social and economic characteristics of provinces in 1995. Summing up, to account for heterogeneity in local labor markets, we include provincial population size and provincial unemployment rate for 28-to-54-years-old males (including natives and immigrants) at two points in time; 1985 and 1990.

Studies on location choices of internal and international migrants reveal that ties of kinship, acquaintanceship, and birth places link former and latter migrants, and influence the destination choices of potential migrants through providing them information about destination labor and housing markets (see Bartel, 1989; Dunlevy, 1991; Zavodny, 1999; Davis et al., 2002; Winters et al., 2001; Bauer et al., 2005; Bauer et al., 2007; Jaeger, 2000; Jaeger, 2007, Fafchamps and Shilpi, 2013). How these migrant ties (or migrant networks) are defined and measured varies across studies. Fafchamps and Shilpi (2013) prefer to capture the impact of migrant networks on location propensities by the fraction of a destination district's population who shares the same ethno-caste, religious and linguistic characteristics with the internal migrant in consideration. Jaeger (2007) introduces three variables to quantify the impact of immigrant concentrations: the share of the state population that comes from the immigrant's region of birth; the share of the immigrant's region of birth population in US that lives in the state; and the share of the state's population that was foreign-born. Bartel (1989) prefers to include the share of the immigrants with the same ethnicity in US that lives in a SMSA to control for supposedly migration cost reducing impact of migrant networks. The migrant stock variables used in Bauer et al. (2007) are similar to those in Jaeger (2007) and are explained in detail previously. What these studies have in common is that the ties which matter most for a potential migrant are those that are formed by sharing the same region/country/district/village of birth, or in short, place of birth. This observation leads us to define migrant networks with regard to ties of birth provinces. We include three migrant network variables into our specification following Jaeger (2007). The first one is the share of the immigrant's birth province group in the population of the destination province; the second variable is the share of the immigrant's birth province population in Turkey that lives in the destination province; and the last one is the share of the foreign-born individuals in destination province population. The first stock variable accounts for the relative size of the network and captures the extent of ethnic goods available to the immigrant in a destination location (Baur et al., 2007; Jaeger, 2007). The ethnic goods component of the network includes besides availability of ethnic foods and music, the availability of people who speak the same language with the immigrant. In Turkish context it is possible to think that linguistic considerations may not affect migrants' location choices; however, migrants from east and south-east parts of Turkey are known to have difficulties in speaking the official language. Thus, the first stock variable to some extent also measures the size of the linguistic enclave in a destination (Jaeger, 2007). The second stock variable measures the amount of information available to the immigrant about a destination relative to other destinations. Since the denominator is the same for all provinces[82], this variable accounts for the impact of absolute size of the immigrant's birth province group in a destination. The second stock variable is supposed to capture the impact of the extent of information available to the potential migrant about housing and labor markets at a destination relative to other destinations. Immigrants may discount the extent of information that they have on labor markets at destination and the extent of assistance that they could get after arrival, and prefer to move to destinations that they know welcome immigrants of all origins. It may be the attitudes of natives against immigrants or the differential services offered to the immigrants and their families that attract migrants to these provinces. The last stock variable captures these effects. In a sense it controls for the herd behavior where the herd consists of immigrants of all origins (regardless of their birth provinces). The third stock variable may be collinear with the second stock measure because immigrant attracting cities like Istanbul, Ankara and Izmir might also account

[82] The second stock variable is measured by dividing the total count of immigrant's birth province group in a destination province to the total count of immigrant's birth province group in Turkey.

for the largest shares of the population of immigrants in immigrant sending cities (Kocaman, 2008). Therefore, in the multivariate analysis we check for the sensitivity of the results by excluding the third stock variable from the regressions. Bauer et al. (2007) and Jaeger (2007) show that the relationship between location propensities and migration networks is non-linear, more specifically of inverted U shape; hence, for all three migrant stock variables we include both a linear and a quadratic term to allow for this possibility.

It may be the case that instead of acquiring information about housing and labor markets at destination and getting help in terms of food, shelter and job referrals upon arrival through former migrants that are linked to potential migrants via birth province and kinship; acquaintances, neighbors, and colleagues in the origin province may assist potential migrants in their location choices. To allow for this possibility, we construct migrant network measures that are conceptually the same with the previous ones but the tie that links former and latter migrants is living in the same origin province before migrating. That is, the first stock variable is defined as the share of a destination population that is from migrants from the same origin province as the potential migrant—with the migrant from 1990 or 2000 census—that moved to the destination between 1980 and 1985, or between 1985 and 1990. The other network variables are constructed analogously and we test the sensitivity of the results to the way we define migrant networks by incorporating this new set of network variables that are based on ties of origin province.

Migration, either international or internal, incurs some substantial costs: travel costs, psychic costs of leaving beloved ones behind, information gathering costs and costs associated with accommodating to a new environment (Bartel, 1989; Jaeger, 2007). Internal migrants may be more sensitive to travel costs associated with visiting kin compared to international migrants as the former involves passing city borders and the latter involves passing country borders. To proxy for migration costs, we take the straight-line distance (in kilometers) between the centers of destination province and the immigrant's province of origin. The marginal cost of moving one unit further for a migrant may decline as the distance between the destination and the origin province increases (Davies et al., 2001; Jaeger, 2007). We include a squared distance term to allow the relation between location propensities and distance to be non-linear.

Cragg and Kahn (1997) show that amenities are important determinants of location choice. Fafchamps and Shilpi (2013) find that better access to amenities measured in terms of higher housing premium, and shorter travel time to the nearest paved road and bank are important pull factors of districts in Nepal. Jaeger (2007) includes in the regressions quadratics in absolute differences in average temperatures and annual average precipitations between the immigrant's country of birth and the US state. He finds that the differences in amenities between states have almost zero effect on location propensities of immigrants in all admission categories (regardless of gender). We do not have information on amenities that provinces provide. However, by including province fixed effects (province specific constants) we may account for the impact of amenities, as province fixed effects, when we pool the data from 1990 and 2000 censuses, control for time invariant attributes of a province like weather, total land area of the province, being on the coast, the amount of resource endowment, etc. Province fixed effect for a destination captures the average impact of factors not controlled for directly—including amenities—on the utility of the destination (Train, 2009). The source of the identification with fixed effects models differs depending on the data set at hand. If the multivariate analysis is based on a single cross-section and province fixed effects are included in the model specification, then the parameters of the model are identified through within province variation in observable covariates (Allison, 2009). In the case of pooled cross-sectional data where province-group dummies are included in the model, the identification comes from within province variation in observable covariates over time (Jaeger, 2007). To escape from dummy variable trap one of the location dummies should be dropped in either of the data sets discussed. Fixed effects methods help to control for omitted variable bias; hence, we prefer to include province specific constants to our model specification. Zavodny (1999), Kaushal (2005) and Aslund (2005) investigate the impact of welfare benefits on migrants' location choices, and couldn't find evidence on differences in welfare generosity among locations inducing systematic location choices. To the best of our knowledge, we do not have variation in welfare benefits among Turkish provinces, neither in the past nor in the present, because the central government considers the country as a unity when planning social welfare programs. Hence, welfare benefits are supposedly ineffective on locational choices of internal migrants and therefore we do not control for welfare benefits.

We have mentioned earlier that source province characteristics also matter in location choice of migrants. Migrants from a source with high income level may view the income level of a destination differently than migrants from a source with low income level (Davies et al., 2001). However, source province characteristics do not vary over alternative destinations; thus, we cannot directly include them as separate regressors in our specification. Davies et al. (2001) argues that there are three possible solutions to account for differences in origin province characteristics of migrants. Firstly, we may ignore the differences in source province characteristics and concentrate only on destination characteristics. However, this approach is restrictive as it implicitly assumes that a location attribute has the same contribution to the utility of a destination for migrants from different sources; although, for migrants from a given source the location attribute may be favorable and for the migrants from another source the location attribute may be undesirable. Secondly, we may interact province dummies with source province characteristics. This will lead to a substantial increase in the number of parameters that needs to be estimated as there are 66 alternatives and numerous origin characteristics. The second approach would be infeasible to apply and most likely result in convergence problems. Thirdly, we may use relative measures of location attributes between the destination and origin province. Davies et al. (2001) via incorporating destination-to-origin ratios of location attributes allows the effect of location characteristics to vary over origin states. As the ratio exceeds one, the relative difference between destination and origin increases, and this leads to a higher influence of the location characteristic on locational propensity. Fafchamps and Shilpi (2013) use differences in location attributes between the destination and the origin to control for differences in source district characteristics among immigrants. This method corresponds to taking logarithmic transformation of destination-to-origin ratio of location characteristics such as population, housing price premium, average district income and consumption in their study. Both methods applied by Fafchamps and Shilpi (2013), and Davies et al. (2001) require symmetric responses to changes either in destination or origin source characteristics, and in this sense, these methods are also restrictive. However, applying the second approach is infeasible; thus, we adopt the third option and create variables that take the differences in location characteristics between destination and origin provinces.

The data limitations in this study may cause some problems. Firstly, for internal migrants we observe their province of origin and province of destination, and between the two observations there is 5 year lag. During this time period the migrant may have moved more than once and eventually decided to settle in the province that we observe at the end of the fifth year. If the migrant has the same set of information regarding the destination alternatives before his first move and decided not to migrate to his ultimate choice in the first place, then we may overestimate the impacts of province attributes which are correlated with the final move. Think of an extreme case where all the migrants move more than once during the 5 years prior to the survey date and all chose initially provinces with small concentrations of same birth place individuals, and all ultimately chosen destination provinces have high concentrations of compatriots. In this scenario, assuming that before the first move migrants know the spatial distribution of their birth place group over provinces, we overestimate the impact of migrant networks; actually, we predict a wrong direction for the impact of migrant stocks on location propensities. We don’t have any viable approach to counteract this possibility; hence, we simply assume that migrants stay in their intended locations for a long period of time or at least for 5 years. Secondly, we estimate our conditional logit model using the pooled census data from 1990 and 2000, mainly to control for time constant province characteristics via incorporating province dummies. In this case, the model imposes a restriction as the parameters are not allowed to vary across time. Some location characteristics may have gained importance over a decade, and some others may have lost influence on location decisions of migrants. We can check whether the parameter estimates are stable over a decade in two ways: firstly, with pooled census data we can interact each location characteristic with two dummy variables; one for year 1990 and one for year 2000[83]. In this way, we end up with two sets of parameter estimates that allow the impact of location attributes to vary across time. Secondly, we can run separate regressions on each census data to see whether the results are consistent over a decade while relative economic and demographic conditions of locations may be changing from one census to the other. We prefer the second approach.

Thirdly, Turkey experienced an increase in the number of provinces over the period 1985-2000. The number of provinces were 67, 73, and 81 in 1985, 1990 and 2000 censuses, respectively. The new provinces were counties of the existing provinces and became a province of their own[84]. The process of new city creation did not cause existing old provinces to change names or cease entirely. This process resulted in a change in the borders of the provinces. To track provinces over a period of 15 years, we have two options: i) define the labor markets as provinces in 2000 which results in the migrant to have a choice set of 80 alternatives; ii) define the labor markets as provinces in 1985 which presents migrants 66 alternatives among which they need to choose one. The first approach is problematic in two ways: first, it requires the migrants to perfectly foresee that a county which presents a small labor market today will become a province in the future and will have a boom in job opportunities due to the city formation process; secondly, for a migrant with a birth province among the last 14 created cities, we are unable to create migrant network variables due to the fact that we don't have the birth county information for observations in 1985 and 1990 censuses[85]. The second approach is not

[83] The dummy for year 1990 takes value one if the migrant had moved between 1985 and 1990 and takes value zero otherwise. The dummy for year 2000 is constructed analogously.

[84] Aksaray, Bayburt, Karaman, Kırıkkale became provinces in 1989 and were former counties of Niğde, Gümüşhane, Konya, and Ankara, respectively. Batman and Şırnak were separated from Siirt and became provinces in 1990. All these cities were created after the 1985 census and were first included as provinces in 1990 census. Bartın and Karabük were former counties of Zonguldak and became provinces in 1991 and 1995, respectively. Ardahan and Iğdır were separated from Kars in 1992. Yalova, Kilis, Osmaniye and Düzce were former counties of İstanbul, Gaziantep, Adana and Bolu, respectively. The latter set of provinces were first introduced as provinces in 2000 census.

[85] Plus, we do not have the county of residence information in 1985 census which would also be required to create migrant network variables in the last founded 14 cities.

free of problems, either. If we imagine the province that was created after 1985 as a county of its former city, and accordingly define the choice set for a migrant to have 66 alternative provinces, then the migrant enclave in a destination would constitute of the former migrants from the province that was split into two and the county that emerged as a new province out of the existing one. On one hand, the outflows of migrants from the newly created province may be directed to destinations that could not be predicted by the joint spatial distribution of the former migrants from the old and new province; however, the migrant networks created by the former migrants from the county—which eventually became a province—may be a good predictor of destination choices of migrants from the newly founded province, and we are unable to differentiate the migrant network of the new province from the migrant network of the old province. On the other hand, it might be the case that the city formation process induces high in-migration to a province that was formerly a county of an existing province since the process involves a significant increase in job openings (Bengin, 2016, para. 2). If the boom in the economy of the newly created province results in inflow of migrants which is uncorrelated with the existing migrant networks in the newly created province[86], then one can simply misevaluate the observational evidence and conclude that migrant networks do not affect location choices of potential migrants. To capture the pull effect of job creations in a newly founded province within our estimation strategy one needs to include to the specification a dummy which takes value one if the destination province contains a county that eventually became a province, and takes value zero otherwise. Based on the above discussion, we prefer to define labor markets as provinces in 1985 with the migrant having the possibility to choose among 66 alternative provinces.

The conditional logit model relies on *independence from irrelevant alternatives* assumption which requires that the ratio of choice probabilities between any two destinations is independent of other alternatives (Train, 2009). Since we let all the provinces in Turkey to be in the choice set, the possibility of existence of alternative provinces that are not in the choice set becomes irrelevant. Hence, *independence from irrelevant alternatives* assumption is trivially satisfied.

We discuss now some potential threats to the model specification. Firstly, values attached to the attributes of destination provinces may vary over immigrants. If immigrants'

[86] Actually, it is the migrant enclaves present in the old province which was split into two as we could not measure the size of the migrant networks in the newly emerging province that was formerly a county. If the old province was not a favorable destination location for immigrants which is suspected to be true for provinces located especially in the eastern and south-eastern parts of the country, the large inflows of migrants to the newly created province out of the existing one would be uncorrelated with the migrant enclaves in the old province.

tastes over attributes of alternatives vary with respect to immigrants' observed characteristics, then by interacting province attributes with the observable traits of immigrants, which are suspected to induce differences in utility levels between alternative provinces[87], conditional logit becomes a suitable model to capture taste variations (Train, 2009). However, if tastes vary with respect to unobserved characteristics of immigrants, then the assumption of errors being independent and identically distributed over alternatives cannot be satisfied which leads to model misspecification (Train, 2009). In our context, immigrants with low language capabilities may have high costs to migrate to provinces where their migrant enclaves are not highly concentrated; hence, they may prefer provinces where a large number of earlier settled compatriots exist. If we had the opportunity to observe language abilities of immigrants, we simply would have interacted the migrant network variable with language capability of the immigrant. However, the census data does not contain information on language capabilities of individuals, therefore the interaction term will end up in the error term which causes errors for different alternatives to be correlated and have different variances[88]. For this specific scenario, the first stock variable by measuring the size of the linguistic enclave in a destination, accounts for differences in tastes of migrants based on unobserved language capabilities. To control for differences across migrants in the values and importance they attach to location attributes, we include individual fixed effects to equation (1)[89]. Individual fixed effects also control for any effect on utility of destinations due to source province characteristics since origin province

[87] Since immigrant characteristics do not vary over alternative locations, there are two ways to incorporate traits of immigrants into conditional logit model: i) normalize the coefficient of the immigrant trait to zero for one alternative location and interpret the remaining coefficient estimates of immigrant's characteristic as the impact of the immigrant trait on an alternative location relative to the location for which the impact is normalized to 0. ii) interact the location attribute with the immigrant characteristic; in this case, there is no need to normalize any of the coefficients of the trait variable to zero. Since location attributes vary over alternatives, the difference in utility levels varies with the immigrant trait (Train, 2009).

[88] Simplify the model in equation (1) and let the utilities depend only on migrant networks in a location and the distance of the location to the place of origin plus a stochastic error term that varies both over individuals and locations: $U_{ij} = \alpha_i Mig_{ij} + \beta dist_{ij} + \varepsilon_{ij}$. The subscript i in the coefficient of migrant network variable is included to allow the value of migrant network to vary over immigrants. We assume that the variation in immigrant tastes over provinces is partly explained by the variation in immigrants' language proficiencies. We can decompose the network effect into two: an average effect and an immigrant specific component—a deviation around the mean that differs across individuals—. Let $\alpha_i = \alpha + \gamma lang_i$ where the latter term controls for the language capability of an immigrant. When we plug α_i into the above equation we reach: $U_{ij} = \alpha Mig_{ij} + \beta dist_{ij} + \gamma lang_i Mig_{ij} + \varepsilon_{ij}$. Since we do not observe language capabilities in census data, the interaction term ends up in the new error term $\tilde{\varepsilon}_{ij} = \gamma lang_i Mig_{ij} + \varepsilon_{ij}$. The new error terms for different alternatives are correlated and have different variances. To see that: $Cov(\tilde{\varepsilon}_{ij}, \tilde{\varepsilon}_{ik}) = Cov(\gamma lang_i Mig_{ij} + \varepsilon_{ij}, \gamma lang_i Mig_{ik} + \varepsilon_{ik}) = Cov(\gamma lang_i Mig_{ij}, \gamma lang_i Mig_{ik}) + Cov(\gamma lang_i Mig_{ij}, \varepsilon_{ik}) + Cov(\varepsilon_{ij}, \gamma lang_i Mig_{ik}) + Cov(\varepsilon_{ij}, \varepsilon_{ik}) = \gamma^2 Var(lang_i) Mig_{ij} Mig_{ik}$. The covariance between new error terms is conditional on observable location attributes, and orijinal error terms ε_{ij} and ε_{ik} are orthogonal to observable location characteristics. Since language capabilities vary over immigrants, the resulting term is not equal to zero. To see that errors do not have identical distributions: $Var(\tilde{\varepsilon}_{ij}) = Var(\gamma lang_i Mig_{ij} + \varepsilon_{ij}) = Var(\gamma lang_i Mig_{ij}) + Var(\varepsilon_{ij}) = \gamma^2 Mig_{ij}^2 Var(lang_i) + Var(\varepsilon_{ij})$. This sum varies over alternatives as migrant networks vary over alternatives. Hence, errors are not identically distributed over alternatives.

[89] A crucial point is that for individual fixed effects to control for omitted variable bias due to heterogeneity in unobserved individual characteristics, the unobserved individual traits should be constant across alternative destinations.

characteristics can be thought of as traits of migrants that do not vary across alternatives (Fafchamps and Shilpi, 2013).

Another critical issue is related with achieving correct inference. The method applied in this study creates patterns of positive and negative correlations in error terms across alternatives for a migrant. A migrant goes to only one location among the alternatives and this creates interdependence across observations for the immigrant. As an example, imagine that a migrant is equally likely to migrate to any province in the choice set and he chooses one of the alternatives randomly. Since there are 66 provinces in migrant's choice set, probability of choosing one of them is $P(y_{ik} = 1) = \frac{1}{66}$. Then for the alternative which is randomly chosen by the migrant, the error term is $\varepsilon_{il} = 1 - P(y_{il} = 1) = 1 - \frac{1}{66} = \frac{65}{66}$. For the other alternatives, the error terms take the value $\varepsilon_{ij} = 0 - P\left(y_{ij} = 1\right) = 0 - \frac{1}{66} = -\frac{1}{66}$. The unchosen alternatives, thus, have positively correlated residuals. The correlation between the residuals of chosen and unchosen alternatives is negative. The main problem stems from the presence of negative correlations in errors across location choices for an immigrant (Fafchamps and Shilpi, 2009). Individual fixed effects capture some of the correlation in the error terms across different alternatives since including individual fixed effects accounts for systematic taste variation that depends on unobserved individual characteristics that do not vary over alternatives. If the unobserved individual characteristics would have affected all the choices for a migrant in the same way, individual fixed effects would absorb the common shock and the remaining residuals would have zero within-cluster correlation (Cameron and Miller, 2015). However, having both positively and negatively correlated residuals renders individual fixed effects insufficient to absorb away the whole within-cluster error correlations. Hence, to correct for this interdependence across observations relative to a migrant, we need to cluster standard errors at individual level.

Including individual fixed effects and clustering standard errors at individual level may not ensure correct inference. Turkey has experienced an armed conflict (with the terrorist organization known as PKK) which resulted in deaths of thousands of ethnic Turks and Kurds which still continues to harm citizens of the country. The main aim of Kurdish terrorists is stated as the establishment of an independent ethnic state in the area which is located partly in South East Turkey, North of Iraq and Syria, and Western Iran (Öcal and Yıldırım, 2010). 1984 was the year that Turkish state had its first martyr to the terrorist attacks and the number of armed attacks by the terrorists increased dramatically in the second half of 1980s and in 1990s ("PKK'nin Kanlı Tarihi", 2016, para. 12-15). The armed attacks are mainly concentrated in eastern and south-eastern regions of Turkey. The severity of the attacks caused thousands of individuals to leave their birth districts and move to western parts of the country during 1980s and 1990s (Yıldırım and Öcal, 2013). If the destination choices of migrants from the same origin province are correlated, then clustering standard errors at individual level would not be sufficient to achieve correct inference. Immigrants originating from the same province have much in common and some of these similarities are unknown to the researcher and may correlate migrants' location choices. To correct for this possibility, we cluster standard errors at origin province level[90]. It is tempting to imagine that the factors that cause correlated location choices of migrants from the same origin province in 1980s are completely irrelevant to migrants' location choices from the same origin province a decade later. Then, it would be possible to cluster standard errors at origin province*year level which results in 134 clusters. However, fear of terrorism is suspected to be a push factor that correlates location choices of migrants from the same origin province both in 1980s and 1990s. Hence, we separate the observations into 67 groups and cluster standard errors by origin province.

Provinces that were targeted by terrorist attacks in the East and Southeast Turkey had experienced downgrade in economic conditions and the migrant enclaves in these provinces responded to terrorism as well. One may falsely conclude that migrant networks are positively associated with migrants' location propensities based on observational data; though it may be the deterring impact of terrorism on migration that migrant enclave measure captures. To isolate the impact of terrorism from other location characteristics on immigrants' locational choices, we include a dummy which takes value 1 if the province suffers from terrorist attacks and takes value 0 otherwise. To identify the impacts of terrorism and job creations due to formation of new cities, we need to use cross province variation in the dummy variables that control for the relevant effects. However, in a province fixed effects model with pooled census data identification comes from within province variation in covariates over time; hence, it is not possible to identify these impacts[91]. In single cross sectional analysis, we can either include province dummies to control for differences in unobserved destination characteristics—includes whether a province is affected from terrorist attacks and whether a province is split

[90] Clustering standard errors at origin province level encompasses clustering standard errors at individual level.

[91] If terrorism and new city formation have the same influence on location choices of immigrants in late 1980s and late 1990s, then location fixed effects would capture these impacts (Allison, 2009). Though, it is a strong assumption to believe in since the pull impact of city formation is most likely high in the short run when the city is newly founded and loses its strength as time passes (as available job positions are getting occupied). Almost half of the cities were created before 1990; hence, it is possible to observe a declining impact of city formation process on location propensities over time. On the other hand, since terrorism is brutal in South-eastern and Eastern Turkey during 1980s and 1990s, it is possible to imagine the deterring impact of terrorism to be constant over time. In that case, province fixed effects would account for the difference in location propensities due to safety issues.

into two that results in job creations—, or include dummy variables which control for impacts of terrorism and job creations on location choices of migrants since the identification comes from both within-province and cross-province variation in covariates in single cross-section discrete choice models (Jaeger, 2007). Based on findings of Öcal and Yıldırım (2010), we include a dummy variable that takes value 1 for provinces Diyarbakır, Mardin, Siirt, Bitlis, Hakkari, Van, Tunceli and Artvin; and takes value zero otherwise[92]. In these provinces, the average number of fatalities in a year due to ethnic terrorism during the period 1987-2001 is more than 9.733, and according to this definition ethnic terrorism is most brutal in these cities compared to other cities in Turkey. We can estimate the impact of job creation due to new city formation process in province fixed effects model with pooled census data by allowing the impact to vary over time: new job opportunities in cities created between 1985 and 1990 have influence only on migrants' location choices who move between 1985 and 1990; similarly, new job opportunities in cities created between 1990 and 2000 are influential only on the location propensities of migrants that move between 1995 and 2000. It is obvious that the location decisions of migrants that had moved between 1985 and 1990 are orthogonal to changes in labor market characteristics of cities that are going to be created 5 to 10 years later than their moves occurred. The pull impact of new jobs in cities that were created between 1985 and 1990 are assumed to diminish for migrants that are going to move between 1995 and 2000. In this way, the variable that captures the impact of new job openings vary over time.

2.3 Data and Descriptive Statistics

The Turkish Statistical Agency (TÜİK) makes publicly available the 5% random sample of the population censuses from years 1985, 1990 and 2000. We use 5% censuses from 1990 and 2000 to determine the internal migrants. Then, we match internal migrants who had changed their province of residence between 1985 and 1990 with possible destinations and their characteristics measured in 1985 census. Similarly, internal migrants who had moved between 1995 and 2000 are matched to locations and their characteristics measured in 1990 census. The location characteristics are observed before the migration had occurred. Hence, simultaneity issues are not much of concern. The census questionnaire asks besides the current place of residence and place of residence five years ago, detailed questions about demographics such as

[92] Actually we include this dummy variable only to specifications in Table 2-3 where we run robustness checks and omit province-group dummies from the model specification. It will be explained in more detail later, but shortly including province fixed effects causes convergence issues which lead us to create groups of similar provinces with respect to socioeconomic and demographic characteristics and instead include province-group dummies to the location choice models.

the last finished schooling, gender, age, marital status, occupation, and unemployment. The 2000 census adds to the set of questions in 1990 census the motives for migration.

The 5% census from 1990 contains 2,864,207 observations from all 73 provinces in Turkey. A total of 598,067 individuals live in a province which is different than their province of birth. 204,949 individuals changed their province of residence in the last five years[93]. Around 7.2% of the observations migrated internally within the last five years. There are many motives for migration including finding a better job, getting education and marriage. The determinants of location choices for migrants with different migration motives may differ as well. Work migrants are suspected to be more sensitive to differences in labor market conditions in possible destinations; hence, our study focuses on work migration. 1990 census contains 25,325 male internal migrants who are between ages 28 and 54, are not either students or retirees, and are not civil servants or members of Turkish armed forces. Non-migrant male group is similarly defined and has a total count of 319,503. The migrants are on average younger, better educated and more likely to be literate, less likely to be household heads and married, less likely to be self-employed or unpaid family workers, more likely to be wage earners and unemployed compared to non-migrants. The age difference between the migrant and non-migrant groups reflects the fact that migrants generally move when they are younger so that there is more time left to collect the returns to migration. Since migrants and non-migrants differ on observable characteristics, there is a chance to have heterogeneity in unobservable characteristics as well. If the traits that are unobserved to the econometrician help determine whether a person moves or stays and also are correlated with the determinants of location choice, then focusing on only migrants to estimate location propensities may cause sample selection bias. Therefore, as a robustness check we estimate the impact of choice attributes based on a sample consisting of both migrants and non-migrants.

5% random sample of 2000 population census contains 3,444,456 observations from all 81 provinces in Turkey. 239,727 of them settled in a different province than their province of origin. A total of 854,502 individuals left their birth province. When it comes to the motives for migration, among adult male migrants who are at least 15 years-old the largest group is work migrants with a share of 52%, it is followed by education related migration with 13% and migration dependent on a household member with 8%. Migration due to marriage only

[93] The information regarding migration within last five years is available for individuals who are at least 5 years-old. Migration status with respect to birth province is known for any individual regardless of their ages. The descriptive analysis and multivariate analysis disregard individuals born in foreign countries, individuals who migrated to foreign countries or in-migrated from foreign countries within the last five years.

constitutes 1% of adult male migrants. When we look at the motives for migration of adult female migrants, the largest group moves since one of the household members migrates. It is followed by work related migration with a share of 22%. Share of education related migration is on par with adult male migrants. However, unlike adult males, marriage is an important motive for migration for females: 19% of adult females change province of residence within last five years to accompany their spouses.

The estimation sample consists of adult male work migrants who are 28-to-54-years-old, are not either students or retirees; hence, have a possible connection to labor markets. We exclude civil servants and soldiers since their location choices may be exogenous to socio-demographic and labor market characteristics of locations. Knowing the motives for migration helps us pinpoint migrants who desire to find a better job by migrating. We can further restrict the estimation sample in 2000 census to individuals who migrate in order to search for a job or find a job. There are 16,655 records of internal migrants who satisfy the abovementioned restrictions in 2000 census data. 28-54 years old non-migrants who are not students or retirees, and are not civil servants or soldiers have a total count of 432,688. Some demographic characteristics of 28-54 years old migrants and non-migrants are very similar: on average both groups are secondary school graduates and are equally likely to be literate. Some characteristics vary hugely between the groups: there is more than 25 percentage points difference in wage earner rates between migrant and non-migrant groups; vast majority of migrants (around 64%) are wage earners. Other characteristics follow the pattern in 1990 census: migrants are younger, less likely to be married and household heads, less likely to be employers or self-employed or working as unpaid family worker, and more likely to be unemployed. The unemployment rates increase dramatically between 1990 and 2000 for both migrants and non-migrants. The unemployment rate for 28-54-years-old male migrants is 6.8% and the corresponding figure for non-migrants is 4.9% in 1990. A decade later the unemployment rates increase to 13.8% and 12.4% for migrants and non-migrants, respectively. The significant decline in the economic performance of the country during late 1990s may bring about its own migration dynamics. Therefore, it is necessary to investigate the determinants of location choice separately for years 1990 and 2000.

Table 2-1 presents the descriptive statistics for all variables used to estimate migrants' likelihood to move to a destination. We report average (over immigrants) of the differences in a variable between destination and origin provinces; that is, the variables in Table 2-1 are of the form $\Delta_{ij}^{x} = x_j - x_i$ where x is the choice attribute, i is the province of origin and j corresponds to one of the remaining 66 provinces. For example, let x measure unemployment rate in a province; for actual destination of a migrant, Δ_{ij}^{x} is the difference in unemployment rates (in %) between the chosen province and origin province of the migrant. We take average of Δ_{ij}^{x} over all immigrants for the actual destination in columns (1) and (4). Similarly, columns (2) and (5) present the average of Δ_{ij}^{x} over all immigrants for the remaining 65 alternative destinations. Columns (3) and (6) present t statistic for the test of equality of means.

The immigrants both in 1990 and 2000 move to provinces in which the immigrant's birth province group constitutes a smaller percent of population in comparison to the percent of origin province population that is from immigrant's province of birth. More than half of migrants in both years made the move out of their birth provinces where the immigrants' birth province groups are highly concentrated; thus, observing such a difference between birth province shares in populations of destination and origin provinces is expected. On the other hand, the alternative destinations, on average, have much smaller population shares due to immigrant's birth province relative to that of origin province. The difference in population shares from immigrant's birth province between actual and alternative destinations is statistically significant at 1% level. Hence, migrants prefer to migrate to provinces that unconditionally have higher percent of population that is from immigrant's birth province. The same pattern applies for the migrant network variable that measures the percent of immigrant's birth province population that is living in a destination in both cross-sections: migrants' actual destinations, on average, have fewer number of individuals that are from immigrants' birth provinces than origin provinces have. The difference in number of individuals from immigrant's birth province between actual and alternative destinations is statistically significant at 1% level which implies that migrants move to destinations that unconditionally contain more people who share the same birth province with them. In both cross-sections, foreign-born individuals, on average, make up a larger share of actual destination populations relative to province of origin. Alternative destinations, on average, are less dense in terms of foreign-born settlers relative to origin province. The difference in all three network variables between actual and hypothetical destinations is large in magnitude and statistically significant at 1% level in both years. Indeed, the differences in all variables between actual and alternative provinces are statistically significant at 1% level in each year. When the network variables are defined based on sharing the same origin province with former migrants, the differences between actual and alternative destinations is small; though strongly statistically significant. This reveals that former individuals from the same origin province with the current migrants, on average, are equally likely to move to any possible province in Turkey.

The observational evidence suggests that unemployment rates are, on average, higher in actual destinations than in the origin province for 1990 cross-section of migrants. Settling in alternative destinations, on average, would have reduced the unemployment rate. The comparison of means in actual and alternative provinces shows that migrants move to provinces that have unconditionally higher unemployment rates in 1985. The pattern changes for the 2000 cross-section of migrants. Unemployment rates are lower in actual destinations relative to origin and alternative provinces. Alternative measures of labor market performance reveal that migrants prefer provinces with a higher nonagricultural employment rate and a lower nonagricultural unemployment rate relative to origin and alternative provinces in both years. The association between labor market performance and migrants' location preferences from alternative measures is more in line with the expected responses of migrants to labor market characteristics of destinations. Actual destination choices of migrants, on average, are more populous and denser than origin and alternative provinces in both cross-sections. There is, on average, 45-to-55% increase in population size between the province of origin and actual destination in 1985 and 1990, respectively[94]. Moving to alternative destinations, on average, would have reduced the population size by 43-to-44% relative to province of origin in 1985 and 1990, respectively. The actual destinations are on average 155-to-176% larger with respect to population size than alternative destinations in 1985 and 1990, respectively. Actual destinations, on average, are closer to migrants' origin provinces than alternative destinations and the difference is large in magnitude (around one third of a standard deviation) and strongly statistically significant.

To sum up, migrants prefer to move to provinces with: a higher concentration of same birth province individuals relative to alternative provinces; a higher unemployment rate and nonagricultural employment rate, and a lower nonagricultural unemployment rate relative to origin and alternative destinations; a larger population and population density relative to origin and alternative destinations; and a smaller distance to the origin province relative to alternative provinces.

2.4 Results

Table 2-2 presents the coefficient estimates from our main specification for 28-54-years-old male work migrants, Tables 2-3 and 2-13 present results from alternative specifications. We

[94] The average percentage difference in population sizes between actual destination and origin province is calculated by the formula: $(e^b - 1) * 100$; where b corresponds to the mean difference in log population sizes between actual destination and source province of migrants.

use fixed effects conditional logit to estimate the determinants of migrants' location choices. The regressors include a linear and a quadratic term for: immigrant's birth city percent of province population; percent of immigrant's birth city population in province; percent of province population that is from individuals who are born outside the province; and the straight-line distance between destination and origin provinces. To control for labor market characteristics, we include the unemployment rate and population size of province. To allow source province characteristics to play a role in migrant's location choice, differences between destination and origin province attributes are included as regressors. We account for differences in individual traits that are constant across choices through including individual fixed effects. We cannot estimate the impact of these alternative-constant individual characteristics; though, by controlling for them we alleviate the concerns for having omitted variable bias. Migrants from same origin province may have correlated errors; thus, to achieve correct inference standard error calculation takes into account clustering of observations at origin province level. Standard errors that are clustered at origin province level encompass clustering at individual level; hence, via clustering standard errors by origin province we also achieve to control for the negative and positive correlation pattern in errors across alternatives relative to a migrant.

The most natural way to control for unobserved economic and noneconomic differences between provinces that may affect migrants' location choices is to add province fixed effects to the model specification. Our identification strategy requires dropping the observation that corresponds to the migrant's origin province. Hence, for any migrant the choice set consists of 66 alternatives. Including province fixed effects imply adding 65 alternative specific constants to the model. We believe that the huge increase in the number of parameters and the likely correlation between destination characteristics and destination fixed effects cause maximum likelihood estimations with province fixed effects to declare convergence[95]. To solve the dimensionality problem, we group provinces which are similar in characteristics such as population, socioeconomic development, geography, per capita GDP, per capita output in industry, agricultural output, and urbanization rate[96]. This results in 26 province groups, and regressions include 25 province-group dummies with the group consisting of Balıkesir and Çanakkale as the omitted base category. This approach reduces the number of parameters to be estimated dramatically, and helps to overcome the convergence issues encountered with

[95] It is possible that provinces with favorable observable attributes also have favorable unobserved attributes such as cities with greater perceived economic conditions may provide better access to amenities. Since alternative specific constants control for unobserved characteristics of provinces, it is possible to have collinearity between observable province attributes and province fixed effects.

[96] The groupings of provinces used in the study is provided by TÜİK and is at NUTS-2 level.

province fixed effects models. The resemblance of provinces with respect to observable characteristics within province groupings implies a possible similarity in terms of unobserved province characteristics as well; hence, justifying the use of province-group dummies in place of province dummies. Estimation results omitting province-group dummies are reported in Table 2-3 and there are two main differences relative to the results in Table 2-2: the squared term for the foreign-born percent of province population is estimated to have insignificant effect on location choice and population size is estimated to have a significantly smaller coefficient in all regressions. The main conclusion deduced from this comparison is that unobserved differences between province groupings matter and controlling for them may help identify the parameters. The identification comes from within province-group variation in covariates over time in models estimated with pooled cross-sectional data. The coefficients on location characteristics are identified by within province-group differences in single cross-section models of location choice.

We mentioned previously that almost half of the migrants moved from an origin province that is different than their birth province which implies that for those migrants the choice sets contain their birth provinces. The availability of birth province as an alternative destination may bring about the possibility of return migration (around 29% of migrants in total are return migrants), and those return migrants may do so because there are unobserved birth province characteristics which draw migrants back to their home such as the need to take care of family enterprises; the need to look after parents who suffer from a disease; the negative experiences with former migration moves, etc. The widely available information about labor markets at birth provinces may confound with those unobserved individual-specific-birth-province characteristics. Province-group fixed effects cannot control for those unobserved birth-province pull effects. Thus, to achieve consistent parameter estimation we include a birth province dummy which takes value one if the alternative is the birth province of the migrant, and takes value zero otherwise.

The increase in the number of provinces from 67 to 81 between 1989 and 2000 is a serious issue which requires careful consideration. The problem is that the creation of new provinces may act as positive labor market shocks to the existing provinces which by splitting up led new provinces to emerge. We combine the last 14 provinces with the existing provinces which contained them initially; hence, the newly emerging labor markets in the latter founded provinces may have created unobserved taste for some provinces—the old provinces which the new ones are separated from—after we have measured the location characteristics in 1985 or 1990. The unobserved pull impact of new job opportunities in newly created cities varies across alternatives; therefore, province-group fixed effects cannot control for it. A possible correlation between the unobserved labor market shocks and location characteristics may bias the estimates; hence, we need to control for it. In 1990 cross-section, we include a dummy which takes value one for the alternatives which included counties that became cities between 1985 and 1990, and takes value zero otherwise. In 2000 cross-section, we similarly include a dummy which takes value one for the alternatives which included counties that became cities between 1990 and 2000, and takes value zero otherwise. There is an implicit assumption which implies that there is no impact of new job opportunities that were available during the city formation process for cities founded before 1990 on location choices of migrants who had moved between 1995 and 2000. For the analysis using pooled data from 1990 and 2000, we allow the impact of job creation due to new city formation to vary over time by including three dummy variables: a dummy that takes value one for provinces that had a border change before 1990 for observations from 1990 census data, and takes value zero otherwise; a dummy that takes value one for provinces that had a border change before 1990 for observations from 2000 census data, and takes value zero otherwise; a dummy that takes value one for provinces that had a border change between 1990 and 2000 for observations from 2000 census data, and takes value zero otherwise.

Another concern is the possibility of fear of terrorism being a confounder in migrants' location propensities. We do not need to explicitly control for the impact of terrorism on migrants' location choices since provinces which are mostly affected by terrorism during late 1980s and 1990s are grouped in same sets of provinces; hence, province-group dummies account for the impact of terrorism.

The univariate analysis showed significant differences between location choices and available alternatives. The multivariate analysis in Table 2-2 confirms that the differences between actual destinations and alternatives are significant once we control for population size, labor market attributes and migrant networks. We begin with the estimation results from the pooled data. We exclude civil servants, soldiers, retirees and students, in addition we drop migrants who moved between 1995 and 2000 for reasons other than search or find a job. The pooled estimation sample consists of 41,980 male work migrants who are 28-to-54-years-old. For each migrant there are 66 alternatives among which he can choose resulting in 2,770,680 observations for the fixed effects conditional logit analysis. The results show that immigrants are more likely to choose locations in which their compatriots are more highly concentrated compared to alternative locations. For two of the three migrant network variables there are diminishing returns to the size of the networks: immigrant's birth city share of province population and province share in immigrant's birth city population have inverted U shaped effects on the probability of choosing a particular province. The chances to migrate to a particular province increases as the difference in an immigrant's birth city shares in that province and origin province increases up to 88 percentage points and declines afterwards. The average marginal effect of a 1% increase in the destination-origin difference in population shares from immigrant's birth city with respect to the results from pooled data, evaluated at the sample mean of differences -1.548574 and average probability of location 0.0149, is a 0.43 percentage points increase in the probability of locating in that particular destination[97]. The impact of percent of immigrant's birth city population in province peaks at a destination-origin difference around 67% and declines afterwards. Evaluated at the sample mean of a destination-origin difference in percent of immigrant's birth city population of -1.595674, the average marginal effect of an increase in the destination-origin difference in percent of immigrant's birth city population by 1% is 0.0003. That is, a 1% increase in the destination-origin difference in the percentage of immigrant's birth city population, on average, increases the probability of a migrant choosing to live in that destination by 0.03 percentage points. Among these two migrant network measures, the first one is more important. This suggests that migrants prefer to choose less populous provinces in which their compatriots make up a larger share of the population rather than moving to provinces where they have more number of individuals who were born in the same city as they were. An increase in the destination-origin difference in foreign-born shares increases the chances of a migrant to settle in that destination with an increasing rate. All migrant network variables and their squared terms have strongly significant coefficient estimates. The immigrant's birth city share and the percent of immigrant's birth city population living in the actual destination is higher than in alternative destinations. In addition, the actual destinations of migrants have higher percentage of province population that is from foreign-born individuals compared to alternative destinations.

Unemployment rate has the expected negative sign and is statistically significant at 1% level in column (1). On average, the actual destination has lower unemployment rate than alternative destinations. Lack of job opportunities is a deterrent in migration decision. A 1% increase in the destination-origin difference in unemployment rates that is caused by an increase in the destination unemployment rate, on average, reduces the probability of migrating to that

[97] The average marginal effect of migrant network variables and distance, evaluated at the sample mean of variables, is calculated by the formula: $\frac{\partial \hat{P}(y_{ij}=1)}{\partial z_j} = [\frac{1}{J}(1-\frac{1}{J})](\hat{\alpha}_z + 2\hat{\theta}_{z^2}\bar{z}/100)$

destination by 0.2 percentage points[98]. Migrants prefer to move to relatively more populous provinces. Provinces with large populations may provide more job opportunities and easier access to information about labor markets as the information may be widely available. This reduces the search costs of potential migrants and increases the returns on job search activities in large cities which results in higher chances for a potential migrant to choose relatively larger cities. In addition, it may be easier for migrants to benefit from their migrant enclaves in large cities: large cities offer more job opportunities; hence, the help from immigrant's compatriots is more likely to yield a desired job position for the potential migrant. The results on unemployment rate and population size together suggest that migrants while deciding on the migration destination take into consideration the economic conditions of locations. One standard deviation increase in the destination-origin difference in log population sizes with respect to the results from pooled sample, on average, increases the likelihood of migrating to this destination by 1.4 percentage points. Distance as expected has negative sign and the impact is precisely estimated. The coefficient on the squared distance has positive sign and is strongly significant which implies that distance has a deterrent effect on probability of migrating to a destination but the deterrent effect is not linear; it is in U shape. That is, as distance between destination and origin increases, the probability of choosing that destination decreases with a decreasing rate. The turning point is reached at a distance between destination and origin province of around 870 kilometers, and the impact of distance on location probabilities becomes positive around 1750 kilometers. However, the sample does not include destination-origin pairs which are as distant as 1750 kilometers; hence, over the range the combined effect of distance on migrants' location propensities is negative. The average marginal effect of a one standard deviation increase in the distance between destination and origin, evaluated at the sample mean of distance between alternative and origin provinces, is a 0.6 percentage points decrease in a migrant's likelihood to locate in that destination.

Once we allow for the parameters to vary across time, most coefficient estimates are stable over a decade except for percent of immigrant's birth city population in province and unemployment rate. Migrants, who had moved between 1995 and 2000, appear to take into consideration the difference in relative size of the network but disregard the difference in absolute size of the network between destination and origin while deciding on the migration destination. The result suggests that 2000 cross-section of migrants care about the amount of available ethnic goods in a province but the extent of information about housing and labor

[98] The average marginal effect of unemployment rate is calculated according to equation (4).

markets in a province relative to alternatives is not influential on their location choice. However, for 1990 cross-section of migrants the percent of immigrant's birth city population in a province has an inverted U-shaped relation with the probability of migration to a province. Foreign-born share of province is more important for 1990 cross-section migrants than 2000 cross-section migrants. Unemployment rate differences between destination and origin appear to be more influential on 1990 cross-section migrants' rather than 2000 cross-section migrants' location choices. In addition, the significance of the coefficient estimate for the unemployment rate differential reduces to 5% level in column (3). Davies et al. (2001) provide as an explanation for the variation in the size of the unemployment rate ratio coefficient (on location probabilities) over the years 1986-1996, the changes in the distribution of unemployment rates over U.S. states that occurred during the eleven years under consideration. In years where the unemployment rate is more evenly distributed across states, there is less information that migrants can make use of in deciding where to locate; hence, the impact of unemployment rate ratio is considerably smaller in these years compared to remaining years. The difference in the magnitude of the coefficients for the unemployment rate differential in columns (2) and (3) is not due to unemployment rates being more evenly distributed over provinces when 2000 cross-section of migrants took migration decisions so that unemployment rate differentials do not provide 2000 cross-section of migrants as much information as they provide to 1990 cross-section of migrants about differences in job opportunities across alternative locations. On the contrary, the variance of province unemployment rate for 28-54-years-old males in 1990 is 3.56 while the corresponding figure in 1985 is 2.48; the means are 4.20 and 3.90 in 1990 and 1985, respectively. The reason of why the effect of unemployment rate differential on location propensities decrease over a decade is unclear.

2.5 Robustness Checks

Results from conditional logit regressions of alternative specifications are presented in Tables between 2-3 and 2-13. Firstly, we test the sensitivity of the results in Table 2-2 to the omission of province-group fixed effects. Since we exclude province-group dummies from model specifications, we explicitly need to control for the impact of terrorism on migrants' location probabilities. We consider the provinces that have an average annual fatality rate for the time period 1987-2001 of more than 9.73 as most affected locations from terrorism and create a dummy which takes value 1 for these provinces and zero for the rest of the provinces (Öcal and Yıldırım, 2010). The main differences from results in Table 2-2 can be summarized as follows: the squared term for the foreign-born share of province population is insignificant at nominal 5% level and the difference in log population sizes has a smaller effect on location propensities in all specifications; the unemployment rate differential appears to be less important for the pooled sample and 1990 cross-section of migrants, and appears to be more important for 2000 cross-section of migrants when province-group dummies are omitted. The significance level of the unemployment rate differential increases to 1% for 2000 cross-section of migrants as well. The inverted U-shaped relationship between location probabilities and relative and absolute sizes of the migrant networks remains constant. The foreign-born share of a province is now estimated to have a linear effect on migrants' location propensities. The estimates for the remaining variables are comparable to the corresponding estimates in Table 2-2 with respect to sign, size and significance. The R-squared in models with province-group dummies are higher than in models that omit province-group dummies. The comparison of results in Tables 2-2 and 2-3 suggests that unobserved differences between province groupings are important and including province-group dummies to the specification helps to identify the parameters.

Next, we re-estimate the determinants of migrants' location choices by replacing unemployment rate differential with nonagricultural employment rate differential in Table 2-4 and with nonagricultural unemployment rate differential in Table 2-5. The coefficient estimates are very similar to those in Table 2-2 in terms of size, sign and significance in these alternative specifications. Although the coefficient estimate is close to zero, nonagricultural employment rate differential has an unexpected negative sign in Table 2-4. The result implies that migrants prefer locations where employed individuals are more likely to be working in agricultural sector; in other words, migrants prefer more rural areas. However, the estimates in Table 2-2 reveal that migrants prefer to move to relatively larger population destinations which is more in line with migration from rural to urban areas. Cross-tabulation of migrants' residential statuses (city center, county center or village) five years prior to their moves by their current residential statuses suggests that rural-out migration is less frequent to city centers by 41%; only 53% of migrants from county centers prefer city centers as destinations and a similar rate (by 57%) applies to migrants from city centers. Migrants from county centers and villages constitute the largest share of migrants by a total of 56%. The observational evidence shows that city centers are not dominant migration destinations. Hence, the negative sign on nonagricultural employment rate may not be unexpected at all considering that migration flows in 1980s and 1990s might have been directed towards less dense (more rural) locations. Regressions in Tables 2-6 and 2-7 present evidence in favor of this possibility.

When it comes to results with nonagricultural unemployment rate differential as the preferred labor market control, all estimates are consistent with those in Table 2-2. The only difference is that nonagricultural unemployment rate differential is estimated to have a smaller impact on migrants' location choices compared to unemployment rate differential. Nevertheless, the size of the coefficient on nonagricultural unemployment rate differential is more stable across time compared to the unemployment rate differential. In both specifications with alternative labor market measures, the significance of the coefficient on the labor market attribute drops to 10% level for 2000 cross-section of migrants. The R-squared of regressions with alternative labor market measures are smaller compared to their counterparts in Table 2-2.

Next, we run regressions where we drop differential in log population size and include differential in population density between destination and origin provinces; plus, in another set of regressions we add to the main specification the differential in log land area between destination and origin provinces. The results are presented in Table 2-6 and Table 2-7, respectively. Once we replace log population size differential with population density differential in Table 2-6, we find that pooled sample of migrants and 2000 cross-section of migrants are more likely to locate where population density is lower compared to alternative destinations, while 1990 cross-section of migrants are more likely to choose relatively denser locations. It is expected to have a positive impact of population density if migrants view dense locations as better performing labor markets; though, greater population density may bring about congestion which may push migrants away. The change in the sign of the population density differential may reflect the impact of increasing congestion in provinces over a decade. In Table 2-7, we see that both 1990 and 2000 cross-sections of migrants prefer less dense areas over alternatives, ceteris paribus. In Tables 2-6 and 2-7, the impact of unemployment rate differential is smaller on migrants' location decisions and for 2000 cross-section of migrants the effect completely vanishes. The influence of foreign-born share of province on the probability of choosing a location is more pronounced in these alternative specifications. Furthermore, the province share of immigrant's birth city population in Turkey is estimated to have a positive, linear and strongly significant impact on a migrant's location choice who had moved between 1995 and 2000. The remaining explanatory variables are on par with those in Table 2-2 in terms of sign, magnitude and significance level.

There is a concern that a possible collinearity between foreign-born share of a province and the province share of immigrant's birth city population may affect the estimation results. Hence, in Table 2-8 we check the sensitivity of the results to the omission of foreign-born share of province population. If there would have been a severe collinearity between these two variables, then omitting the foreign-born share of a province would help to identify mainly the coefficient on province share of immigrant's birth city population. However, all three aspects of the coefficient on province share of immigrant's birth city population—sign, size and significance—are on par with those in Table 2-2. Omitting foreign-born share of province variable, on the contrary, harms identification of parameters as unemployment rate differential has insignificant coefficient estimate for 1990 and 2000 cross-sections of migrants.

In Tables 2-9 and 2-10, we define migrant networks as links that connect former and latter migrants through sharing the same origin province. In Table 2-9, the migrant networks are measured by using the migration history of the immigrant's origin province from the previous census so that the immigrant himself would not be included in the calculation of the migrant networks. In Table 2-10, we allow the migrant himself to be a part of the migrant network calculation; however, in this specification, there is a chance that the migrant himself migrated before his countrymen did. Furthermore, not using anterior data to construct migrant network variables may lead to simultaneity bias. We have seen in the univariate analysis that migrant networks based on the alternative definition are, on average, more concentrated in actual destinations rather than in alternative destinations. Although the difference in mean network sizes in actual and alternative destinations is significant, it is sizably smaller relative to the mean difference in migrant networks that are defined by the birth place of the immigrant. Once we control for population size, unemployment rate and distance, the impact of the first two stock network measures becomes negative, and as the difference in network sizes between destination and origin increases the deterrent impact of networks increase with an increasing rate. The results in Table 2-9 and Table 2-10 show that holding everything else constant, the share of province from immigrant's origin city and the percent of immigrant's origin city population in province is larger in alternative destinations than in actual destinations of immigrants. It implies that immigrants are less likely to move to destinations in which their former or current countrymen are relatively more concentrated. One may interpret these results as the negative network externalities present in provinces which have larger absolute number and population share from immigrants' countrymen, push away potential migrants from choosing these locations. However, attention should be paid before arriving to that conclusion since both specifications in Tables 2-9 and 2-10 have some inherent problems with the definition of migrant networks. Firstly, in Table 2-9 a potential migrant is assumed to live in the same origin province when his countrymen decided to migrate to another location which implies that 1990 cross-section of migrants were living in their same origin provinces in 1980;

and 2000 cross-section of migrants were living in their same origin provinces in 1985. This restriction might have generated a spurious correlation between migrant networks and migrants' location choices. Secondly, in Table 2-10 the definition of migrant networks includes the migration patterns of immigrants whose location preferences were investigated. Hence, simultaneity problems may bias the estimates. On the contrary to the huge differences in the size and sign of the impact of migrant networks in Table 2-2 and Tables 2-9 – 2-10, the remaining explanatory variables have comparable effects on location choices of immigrants. Even the R-squared of the models are not vastly different.

In Table 2-11, we re-estimate the discrete choice model by using only destination attributes as regressors. The implicit assumption in this specification is that migrants regardless of their source locations view choice characteristics in the same way. That is, unemployment rate of a destination affects location propensities of migrants from high and low unemployment sources in the same way. This is the model specification used in Jaeger (2007) and Bauer et al. (2007). The specification in Table 2-11 is more restrictive than our main specification in Table 2-2 (Davies et al., 2001). The results in Table 2-11 are similar to those in Table 2-2 with respect to the direction of the impacts; however, the estimates from the restricted model have larger absolute sizes and the foreign-born share of province now has an inverted U-shaped effect on location probabilities. The average marginal effect of a 1% increase in immigrant's birth city percentage in province population for the pooled sample of migrants, evaluated at the sample mean of immigrant's birth city percent of province population of 1.474146 and average location probability of 0.0149, on average is a 0.57 percentage point increase in the probability of locating in that province. The corresponding average marginal effect is estimated to be lower by 0.14 percentage points in Table 2-2. The most important difference between the results from our main specification and from Jaeger's (2007) method is that all migrant networks have inverted U-shaped relation with migrants' likelihood of locating in a province. This result is consistent with Jaeger's (2007) finding of an inverted U-shaped relation between migrant networks and international migrant's choices among states in U.S.

Lastly, we check the sensitivity of the results to the inclusion of non-migrants to the estimation sample. Omitting non-migrants may result in sample selection bias (Davies et al., 2001); hence, the specifications in Tables 2-12 and 2-13 include 28-54-years-old non-migrant males who are supposed to have a possible connection to the labor market, and are not students, retirees, civil servants or members of Turkish armed forces. Furthermore, choice sets of individuals include their source provinces. Every individual has the same choice set which consists of 67 provinces of Turkey. To control for the unobserved differences between staying and moving, we include to the specification: individual-specific province-of-origin fixed effects in regressions in Table 2-12; and a non-migration dummy in regressions in Table 2-13. Province-of-origin fixed effects capture the effect of push factors for migrants and accounts for the unobserved costs of moving for non-migrants. The push factors help to determine why a migrant decides to move out of his origin province but do not affect his location choice. The unobserved costs of moving includes the psychic and economic costs associated with moving. Non-migration dummy takes value one if the chosen province is someone's province of origin—thus, for migrants the non-migration dummy always takes value zero—and takes value zero otherwise. Non-migration dummy captures the unobserved costs associated with moving. The results on migrant networks in these specifications differ from those in Table 2-2 with respect to the shape of the effect on location probabilities. The variables that measure the relative and absolute sizes of the migrant networks have an inverted U-shaped effect on location propensities for 28-54-years-old male work migrants in our main specification. Once we include non-migrants to the estimation sample in regressions in Tables 2-12 and 2-13, the positive impact of individual's birth city share in province population has an increasing rate while for migrants the relative size of migrant network is estimated to have a diminishing return in Table 2-2. The results from specification with province-of-origin fixed effect show a positive (with an increasing rate) impact of province percent of individual's birth city population on location probabilities for the pooled sample and 2000 cross-section of individuals. The impact of the absolute size of network is estimated to be linear on location propensities of individuals from 1990 census data. However, the specification with non-migration dummy gives consistent results (with those in Table 2-2) with respect to the shape of the effect of province percent of individual's birth city population on location propensities. In both specifications (in Tables 2-12 and 2-13), the coefficient on individual's birth city share of province population is smaller in magnitude relative to the coefficient on the same variable in Table 2-2. The impact of province percent of individual's birth city population is estimated to be larger in specification with non-migration dummy than in our main specification, but comparable in specification with province-of-origin fixed effects. Foreign-born share of province population is estimated to be more important in individual's location choice in specification with non-migration dummy compared to our main specification; however, the size of coefficients on this variable is comparable in specification with province-of-origin fixed effect and in our main specification. The specifications in Tables 2-12 and 2-13 differ significantly with respect to the results they spit out for impacts of labor market and population characteristics. The estimates from specification with province-of-origin fixed effect show that unemployment rate difference between destination and origin is not effective on individuals' location choices for the pooled sample of migrants and non-migrants; is a marginally significant deterrent for 1990 cross-section of individuals and has a negative and statistically significant at 5% level impact on individuals' location probabilities who are from 2000 census data. The corresponding results from the specification with non-migration dummy reveal that unemployment rate difference is always a statistically significant deterrent for location propensities regardless of the estimation sample used to run the regressions. The direction, size and the significance of the coefficient on unemployment rate differential that is estimated in Table 2-13 is consistent with what we have found in our regressions with our main specification. The impact of population size differential is estimated to be lower in the specification with province-of-origin fixed effect while the magnitude of the coefficient on population size differential in the specification with non-migration dummy is on par with the coefficient's size in our main preferred specification. Distance is estimated to have similar deterrent effects in both specifications with province of-origin and non-migration dummies and the size of the coefficient in both specifications is comparable to the corresponding size in our main specification. Both coefficients on province-of-origin and non-migration dummies have very large and strongly significant effects (compared to other explanatory variables) on location probabilities. It implies that unobserved differences between staying and moving are important determinants of location choice and being unable to account for them may bias coefficient estimates. Both the inconsistencies in coefficient estimates of migrant networks, labor market and population characteristics; and the huge difference in R-squared (the models in Table 2-13 have between 5 to 6 percentage points more power in explaining the variation in individuals' location choices) between specification with province-of-origin fixed effect and specification with non-migration dummy suggests that the right specification to use when one wants to include non-migrants and source locations to the regressions is the one with non-migration dummy which is used in their study on migration location choices of American internal migrants among possible states by Davies et al. (2001).

2.6 Conclusion

In this study we try to estimate the determinants of internal migrants' location choices among 67 provinces of Turkey. We focus on 28-54-years-old male work migrants' location preferences. We observe that province-to-province migration is frequent in Turkey both in the past and in the present; hence, quantifying the impact of migration destination's pull factors may help local legislators to predict the extent of migrants that they will host in the future and get prepared in advance. Government officials by predicting the forthcoming waves of migrants to different provinces may try to achieve an efficient distribution of these prospective migrants over provinces with the help of regulatory laws.

The results from our main specification show that internal migrants from both 1990 and 2000 census data respond to differences in migrant networks, labor market and population attributes between locations while deciding on the migration destination. Distance between destination and source province is shown to be a significant deterrent of immigrant's location choice. The variables that capture the relative and absolute sizes of migrant networks in a province have inverted U-shaped relation with the probability of a migrant choosing a province; though, over the relevant range of migrant network variables the net effect is positive. Foreign-born share of a province population has a positive and significant impact on location propensities. The impact, on the contrary to other migrant stock variables, has an increasing return to the size of the foreign-born share of province population. This result reflects the effect of migrant hiring cities like İstanbul, Ankara and İzmir; plus, the migrants' preferences to move to cities that they know welcome all kinds of migrants. The results on migrant network variables together imply that migrants are drawn to cities in which their former compatriots and former migrants from all sources are highly concentrated. Differences in population size and unemployment rate have the expected impact on migrants' location probabilities. Population size differences between migration destinations capture the extent of differences in available job opportunities and the results show that migrants are more likely to move to cities in which economic conditions are relatively better. Unemployment rate differences control for the lack of job opportunities and the results reveal that migrants stay away from cities with relatively higher unemployment rates. Most of the coefficient estimates are stable across time except for the province share of immigrant's birth province population in Turkey and unemployment rate. Having similar results across time, while relative economic and noneconomic conditions were changing across provinces, suggests that the results are not derived by an outlier province at one point in time.

The robustness checks are presented in Tables between 2-3 and 2-13. The results from these alternative specifications show that province-group dummies are important in identifying model parameters. The impact of migrant networks on location probabilities is robust to a change in the measure used to control for labor market and population characteristics; omission of foreign-born share of province population variable from the model; using only destination characteristics as regressors; and inclusion of non-migrants to the estimation sample. The shape of the relation between migrant networks and location probabilities changes for the foreign-born share of province population variable when we use only destination characteristics as regressors. The size of the coefficient estimates changes across alternative specifications but the difference between these estimates and our main specification is not dramatic. Labor market and population characteristics are least robust to changes in model specification while distance, which proxies transportation and psychic costs of moving, is most robust to changes in model specification.

To the best of our knowledge, this study is the first that tries to understand the determinants of migration destination choice of internal migrants in Turkey. The results of this study support the earlier findings of the immense literature on migrants' destination choices. It also presents evidence on similar responses to determinants of location choice by migrants from developing and developed country contexts.

Table 2-1 Descriptive Statistics

Cell contents are relative to the province of origin	1990 cross-section of immigrants: Mean in chosen destinations (1)	Mean in alternative destinations (2)	t-test of difference in means (3)	2000 cross-section of immigrants: Mean in chosen destinations (4)	Mean in alternative destinations (5)	t-test of difference in means (6)
Migrant networks						
Birth place share of province population (in %)	-23.412 (71.913)	-44.601 (45.373)	46.745	-44.332 (61.461)	-55.512 (43.301)	23.384
Percent of birth place population in province	-17.573 (62.208)	-40.084 (38.401)	57.415	-36.620 (53.782)	-50.010 (36.788)	32.014
Foreign-born share of province population (in %)	9.613 (30.820)	-7.753 (21.149)	89.349	12.703 (29.549)	-6.533 (21.122)	83.685
Origin city share of province population (in %)	-81.148 (2.442)	-81.317 (2.406)	10.957	-81.579 (3.579)	-81.791 (3.540)	7.599
Percent of origin city population in province	-92.034 (2.754)	-92.786 (2.083)	43.298	-90.425 (4.412)	-91.463 (3.307)	30.228
Labor market attributes						
Unemployment rate (in %)	0.077 (1.830)	-0.295 (2.167)	32.122	-0.524 (2.013)	-0.308 (2.668)	-13.612
Nonagricultural employment rate (in %)	8.201 (29.528)	-8.238 (23.124)	88.182	9.212 (24.105)	-5.546 (19.115)	78.633
Nonagricultural unemployment rate (in %)	-0.724 (3.234)	0.326 (4.465)	-50.999	-1.550 (3.646)	-0.079 (4.751)	-51.382
Population and distance						
Population size (log)	0.375 (1.517)	-0.563 (1.142)	98.040	0.436 (1.524)	-0.582 (1.142)	85.911
Population density	115.001 (503.161)	-105.659 (301.060)	69.598	177.783 (616.577)	-111.203 (351.680)	60.336
Distance from origin province (in 100 km)	4.963 (3.468)	5.714 (3.161)	-34.245	4.881 (3.400)	5.700 (3.122)	-30.877

Notes: t-test of difference in means column reports the t statistic for the test of equality of means. t-test assumes unknown and unequal population variances. All differences in means are statistically significant at 1% level. Standard deviations are in parenthesis.

Table 2-2 Determinants of location choice - using 28-54 years old male work migrants

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.2847***	0.2856***	0.2862***
	(0.0203)	(0.0233)	(0.0207)
Birth place share of province population (in %) sq. ÷ 100	-0.1621***	-0.1607***	-0.1694***
	(0.0166)	(0.0187)	(0.0163)
Percent of birth place population in province	0.0205***	0.0265***	0.0108
	(0.0066)	(0.0070)	(0.0069)
Percent of birth place population in province sq. ÷ 100	-.0152***	-0.0231***	-0.0060
	(0.0037)	(0.0039)	(0.0040)
Foreign-born share of province population (in %)	0.0396***	0.0524***	0.0300***
	(0.0047)	(0.0051)	(0.0046)
Foreign-born share of province population (in %) sq. ÷ 100	0.0073***	0.0065**	0.0110***
	(0.0025)	(0.0025)	(0.0035)
Labor market attribute			
Unemployment rate (in %)	-0.1439***	-0.1907***	-0.0983**
	(0.0232)	(0.0257)	(0.0475)
Population and distance			
Population size (log)	0.9651***	0.9796***	0.9391***
	(0.0596)	(0.0671)	(0.0586)
Distance from origin province (in 100 km)	-0.3770***	-0.3799***	-0.3814***
	(0.0300)	(0.0311)	(0.0335)
Distance from origin province (in 100 km) sq. ÷ 100	2.1577***	2.2618***	2.0239***
	(0.2250)	(0.2413)	(0.2409)
Pseudo-R^2	0.3980	0.4309	0.3551
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. We control for within-origin-province error correlation by implementing cluster robust variance estimator. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-3 Determinants of location choice – omitting province-group dummies

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.3036***	0.3191***	0.2854***
	(0.0193)	(0.0234)	(0.0194)
Birth place share of province population (in %) sq. ÷ 100	-0.1767***	-0.1856***	-0.1712***
	(0.0158)	(0.0186)	(0.0153)
Percent of birth place population in province	0.0209***	0.0228***	0.0139**
	(0.0067)	(0.0072)	(0.0068)
Percent of birth place population in province sq. ÷ 100	-0.0097***	-0.0138***	-0.0051
	(0.0033)	(0.0038)	(0.0037)
Foreign-born share of province population (in %)	0.0349***	0.0350***	0.0348***
	(0.0020)	(0.0026)	(0.0016)
Foreign-born share of province population (in %) sq. ÷ 100	-0.0023	-0.0058*	0.0028
	(0.0027)	(0.0031)	(0.0034)
Labor market attribute			
Unemployment rate (in %)	-0.1041***	-0.0591***	-0.1437***
	(0.0185)	(0.0221)	(0.0207)
Population and distance			
Population size (log)	0.7614***	0.7561***	0.6694***
	(0.0595)	(0.0696)	(0.0422)
Distance from origin province (in 100 km)	-0.3405***	-0.3462***	-0.3465***
	(0.0346)	(0.0355)	(0.0381)
Distance from origin province (in 100 km) sq. ÷ 100	2.0289***	2.1636***	1.9862***
	(0.2390)	(0.2565)	(0.2555)
Pseudo-R^2	0.3849	0.4182	0.3367
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province of birth fixed effects, a dummy that controls for the impact of terrorism and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-4 Determinants of location choice – alternative measure for labor market condition - 1

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.2851***	0.2890***	0.2871***
	(0.0202)	(0.0235)	(0.0206)
Birth place share of province population (in %) sq. ÷ 100	-0.1624***	-0.1636***	-0.1702***
	(0.0164)	(0.0187)	(0.0162)
Percent of birth place population in province	0.0203***	0.0253***	0.0107
	(0.0064)	(0.0068)	(0.0068)
Percent of birth place population in province sq. ÷ 100	-0.0151***	-0.0227***	-0.0057
	(0.0036)	(0.0040)	(0.0040)
Foreign-born share of province population (in %)	0.0423***	0.0558***	0.0339***
	(0.0051)	(0.0054)	(0.0063)
Foreign-born share of province population (in %) sq. ÷ 100	0.0075***	0.0066***	0.0112***
	(0.0025)	(0.0025)	(0.0035)
Labor market attribute			
Nonagricultural employment rate (in %)	-0.0090***	-0.0149***	-0.0092*
	(0.0024)	(0.0025)	(0.0049)
Population and distance			
Population size (log)	0.9203***	0.9400***	0.8989***
	(0.0557)	(0.0648)	(0.0571)
Distance from origin province (in 100 km)	-0.3765***	-0.3791***	-0.3809***
	(0.0301)	(0.0313)	(0.0338)
Distance from origin province (in 100 km) sq. ÷ 100	2.1541***	2.2611***	2.0169***
	(0.2274)	(0.2461)	(0.2446)
Pseudo-R^2	0.3976	0.4306	0.3550
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-5 Determinants of location choice – alternative measure for labor market condition - 2

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.2811***	0.2833***	0.2850***
	(0.0200)	(0.0232)	(0.0206)
Birth place share of province population (in %) sq. ÷ 100	-0.1590***	-0.1590***	-0.1684***
	(0.0163)	(0.0186)	(0.0161)
Percent of birth place population in province	0.0212***	0.0264***	0.0109
	(0.0065)	(0.0069)	(0.0069)
Percent of birth place population in province sq. ÷ 100	-0.0156***	-0.0234***	-0.0062
	(0.0036)	(0.0039)	(0.0040)
Foreign-born share of province population (in %)	0.0365***	0.0460***	0.0262***
	(0.0049)	(0.0053)	(0.0052)
Foreign-born share of province population (in %) sq. ÷ 100	0.0075***	0.0066***	0.0110***
	(0.0025)	(0.0025)	(0.0035)
Labor market attribute			
Nonagricultural unemployment rate (in %)	-0.0490***	-0.0343***	-0.0476*
	(0.0118)	(0.0115)	(0.0253)
Population and distance			
Population size (log)	0.9304***	0.9253***	0.9465***
	(0.0565)	(0.0652)	(0.0609)
Distance from origin province (in 100 km)	-0.3784***	-0.3816***	-0.3824***
	(0.0301)	(0.0314)	(0.0337)
Distance from origin province (in 100 km) sq. ÷ 100	2.1655***	2.2793***	2.0305***
	(0.2246)	(0.2437)	(0.2405)
Pseudo-R^2	0.3977	0.4303	0.3550
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-6 Determinants of location choice – population density as alternative population control

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.2657***	0.2716***	0.2656***
	(0.0198)	(0.0225)	(0.0204)
Birth place share of province population (in %) sq. ÷ 100	-0.1455***	-0.1488***	-0.1509***
	(0.0163)	(0.0182)	(0.0164)
Percent of birth place population in province	0.0296***	0.0341***	0.0194***
	(0.0070)	(0.0073)	(0.0073)
Percent of birth place population in province sq. ÷ 100	-0.0164***	-0.0238***	-0.0076*
	(0.0037)	(0.0040)	(0.0041)
Foreign-born share of province population (in %)	0.0732***	0.0628***	0.0825***
	(0.0043)	(0.0060)	(0.0064)
Foreign-born share of province population (in %) sq. ÷ 100	0.0067***	0.0056**	0.0108***
	(0.0024)	(0.0024)	(0.0035)
Labor market attribute			
Unemployment rate (in %)	-0.0723***	-0.1134***	-0.0285
	(0.0175)	(0.0201)	(0.0511)
Population and distance			
Population density	-0.0008**	0.0031***	-0.0034***
	(0.0004)	(0.0009)	(0.0009)
Distance from origin province (in 100 km)	-0.3684***	-0.3725***	-0.3762***
	(0.0309)	(0.0323)	(0.0340)
Distance from origin province (in 100 km) sq. ÷ 100	2.1165***	2.2336***	1.9995***
	(0.2262)	(0.2447)	(0.2417)
Pseudo-R^2	0.3917	0.4249	0.3495
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-7 Determinants of location choice – land area added to the main specification

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.2813***	0.2830***	0.2832***
	(0.0212)	(0.0241)	(0.0213)
Birth place share of province population (in %) sq. ÷ 100	-0.1594***	-0.1587***	-0.1670***
	(0.0172)	(0.0193)	(0.0168)
Percent of birth place population in province	0.0222***	0.0278***	0.0122*
	(0.0068)	(0.0072)	(0.0072)
Percent of birth place population in province sq. ÷ 100	-0.0149***	-0.0230***	-0.0057
	(0.0038)	(0.0041)	(0.0041)
Foreign-born share of province population (in %)	0.0579***	0.0682***	0.0455***
	(0.0054)	(0.0058)	(0.0054)
Foreign-born share of province population (in %) sq. ÷ 100	0.0077***	0.0066***	0.0115***
	(0.0025)	(0.0025)	(0.0035)
Labor market attribute			
Unemployment rate (in %)	-0.1145***	-0.1569***	-0.0385
	(0.0251)	(0.0280)	(0.0556)
Population and distance			
Population size (log)	0.6248***	0.7077***	0.5935***
	(0.0755)	(0.0793)	(0.0883)
Land area (log)	0.6592***	0.5379***	0.6261***
	(0.0896)	(0.1011)	(0.1055)
Distance from origin province (in 100 km)	-0.3796***	-0.3808***	-0.3860***
	(0.0300)	(0.0313)	(0.0330)
Distance from origin province (in 100 km) sq. ÷ 100	2.1744***	2.2657***	2.0595***
	(0.2268)	(0.2430)	(0.2412)
Pseudo-R^2	0.3990	0.4315	0.3562
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-8 Determinants of location choice – foreign-born share of province omitted

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.3099***	0.3164***	0.3045***
	(0.0199)	(0.0239)	(0.0203)
Birth place share of province population (in %) sq. ÷ 100	-0.1815***	-0.1851***	-0.1840***
	(0.0155)	(0.0182)	(0.0156)
Percent of birth place population in province	0.0161***	0.0199***	0.0078
	(0.0062)	(0.0066)	(0.0069)
Percent of birth place population in province sq. ÷ 100	-0.0144***	-0.0216***	-0.0073*
	(0.0037)	(0.0041)	(0.0040)
Labor market attribute			
Unemployment rate (in %)	-0.0911***	-0.0593	-0.0186
	(0.0292)	(0.0388)	(0.0461)
Population and distance			
Population size (log)	1.2221***	1.1929***	1.1842***
	(0.0502)	(0.0583)	(0.0559)
Distance from origin province (in 100 km)	-0.3661***	-0.3722***	-0.3633***
	(0.0306)	(0.0328)	(0.0343)
Distance from origin province (in 100 km) sq. ÷ 100	2.1512***	2.2869***	1.9865***
	(0.2316)	(0.2576)	(0.2443)
Pseudo-R^2	0.3953	0.4274	0.3533
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-9 Determinants of location choice – networks based on living in the same origin province - 1

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Origin city share of province population (in %)	-12.9817***	-26.7224***	-13.5790***
	(2.1540)	(2.5514)	(1.5978)
Origin city share of province population (in %) sq. ÷ 100	-8.8662***	-17.6864***	-9.3261***
	(1.4065)	(1.6615)	(1.0816)
Percent of origin city population in province	-2.5264***	-3.8500***	-1.2757***
	(0.4480)	(0.9559)	(0.30647)
Percent of origin city population in province sq. ÷ 100	-1.6527***	-2.3997***	-0.8630***
	(0.2695)	(0.5467)	(0.1959)
Foreign-born share of province population (in %)	0.0321***	0.0422***	0.0286***
	(0.0038)	(0.0043)	(0.0044)
Foreign-born share of province population (in %) sq. ÷ 100	0.0133***	0.0130***	0.0072*
	(0.0037)	(0.0027)	(0.0041)
Labor market attribute			
Unemployment rate (in %)	-0.1275***	-0.1544***	-0.0869**
	(0.0210)	(0.0246)	(0.0397)
Population and distance			
Population size (log)	0.9775***	1.0301***	0.9137***
	(0.0463)	(0.0630)	(0.0495)
Distance from origin province (in 100 km)	-0.2891***	-0.2540***	-0.2889***
	(0.0294)	(0.0347)	(0.0347)
Distance from origin province (in 100 km) sq. ÷ 100	1.6304***	1.5242***	1.4677***
	(0.1919)	(0.2363)	(0.2034)
Pseudo-R^2	0.3906	0.4230	0.3526
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. The migrant network measures are calculated using migration information from the previous census for each cross-section of migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-10 Determinants of location choice – networks based on living in the same origin province - 2

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Origin city share of province population (in %)	-9.8798***	-12.9610***	-31.2947***
	(3.7223)	(1.4366)	(3.4263)
Origin city share of province population (in %) sq. ÷ 100	-6.7975***	-9.0300***	-19.9757***
	(2.4297)	(0.9727)	(2.1539)
Percent of origin city population in province	-1.9388***	-1.2687***	-2.3732***
	(0.4149)	(0.2758)	(0.8775)
Percent of origin city population in province sq. ÷ 100	-1.3584***	-0.8945***	-1.5948***
	(0.2688)	(0.1771)	(0.5300)
Foreign-born share of province population (in %)	0.0346***	0.0379***	0.0297***
	(0.0024)	(0.0032)	(0.0038)
Foreign-born share of province population (in %) sq. ÷ 100	0.0072	0.0064	0.0050
	(0.0063)	(0.0051)	(0.0049)
Labor market attribute			
Unemployment rate (in %)	-0.1041***	-0.1131***	-0.0822**
	(0.0227)	(0.0235)	(0.0342)
Population and distance			
Population size (log)	0.9396***	0.9757***	0.9245***
	(0.0445)	(0.0466)	(0.0530)
Distance from origin province (in 100 km)	-0.2698***	-0.2433***	-0.2080***
	(0.0245)	(0.0348)	(0.0300)
Distance from origin province (in 100 km) sq. ÷ 100	1.4786***	1.3459***	0.9860***
	(0.1822)	(0.2266)	(0.1878)
Pseudo-R^2	0.3956	0.4268	0.3586
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. The migrant network measures are calculated using migration information from the same census for each cross-section of migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-11 Determinants of location choice – using only destination characteristics as regressors

	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.3880***	0.3743***	0.4197***
	(0.0335)	(0.0317)	(0.0407)
Birth place share of province population (in %) sq. ÷ 100	-0.2358***	-0.2269***	-0.2639***
	(0.0260)	(0.0241)	(0.0303)
Percent of birth place population in province	0.0762***	0.0961***	0.0523***
	(0.0090)	(0.0083)	(0.0115)
Percent of birth place population in province sq. ÷ 100	-0.0819***	-0.1032***	-0.0622***
	(0.0066)	(0.0065)	(0.0091)
Foreign-born share of province population (in %)	0.0812***	0.0813***	0.0648***
	(0.0080)	(0.0079)	(0.0111)
Foreign-born share of province population (in %) sq. ÷ 100	-0.0794***	-0.0619***	-0.0648***
	(0.0104)	(0.0134)	(0.0169)
Labor market attribute			
Unemployment rate (in %)	-0.1733***	-0.2053***	-0.1073**
	(0.0239)	(0.0260)	(0.0481)
Population and distance			
Population size (log)	0.9893***	1.0324***	0.9451***
	(0.0499)	(0.0554)	(0.0553)
Distance from origin province (in 100 km)	-0.4019***	-0.4068***	-0.3998***
	(0.0312)	(0.0305)	(0.0369)
Distance from origin province (in 100 km) sq. ÷ 100	2.3795***	2.5049***	2.2215***
	(0.2117)	(0.2190)	(0.2456)
Pseudo-R^2	0.3969	0.4292	0.3542
Number of individuals	41,980	25,325	16,655
Number of observations	2,770,680	1,671,450	1,099,230

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old adult male work migrants. Standard error calculation takes into account possible error correlations within-origin-provinces. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-12 Determinants of location choice – including non-migrants to the estimation sample - 1

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.0439***	0.0497***	0.0398***
	(0.0018)	(0.0023)	(0.0025)
Birth place share of province population (in %) sq. ÷ 100	0.0141***	0.0148***	0.0133***
	(0.0022)	(0.0025)	(0.0023)
Percent of birth place population in province	0.0238***	0.0329***	0.0203***
	(0.0038)	(0.0047)	(0.0047)
Percent of birth place population in province sq. ÷ 100	0.0051**	0.0021	0.0056**
	(0.0025)	(0.0029)	(0.0024)
Foreign-born share of province population (in %)	0.0344***	0.0516***	0.0333***
	(0.0084)	(0.0083)	(0.0061)
Foreign-born share of province population (in %) sq. ÷ 100	0.0517***	0.0539***	0.0508***
	(0.0040)	(0.0043)	(0.0048)
Labor market attribute			
Unemployment rate (in %)	-0.0036	-0.0787*	-0.0802**
	(-0.0036)	(0.0408)	(0.0356)
Population and distance			
Population size (log)	0.4782***	0.4930***	0.4604***
	(0.0644)	(0.0689)	(0.0825)
Distance from origin province (in 100 km)	-0.3481***	-0.3372***	-0.4230***
	(0.0439)	(0.0449)	(0.0508)
Distance from origin province (in 100 km) sq. ÷ 100	1.8265***	1.9036***	2.1657***
	(0.3112)	(0.3279)	(0.3408)
Province of origin dummy	5.5994***	5.1486***	5.8994***
	(0.1084)	(0.1059)	(0.1164)
Pseudo-R^2	0.9193	0.8982	0.9378
Number of individuals	794,171	344,828	449,343
Number of observations	53,209,457	23,103,476	30,105,981

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old male work migrants and non-migrants. We control for within-origin-province error correlation by implementing cluster robust variance estimator. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, province-of-origin fixed effect, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

Table 2-13 Determinants of location choice – including non-migrants to the estimation sample - 2

Province difference in	Pooled data (1990 & 2000) (1)	1990 cross-section (2)	2000 cross-section (3)
Migrant networks			
Birth place share of province population (in %)	0.0285***	0.0223**	0.0355***
	(0.0070)	(0.0089)	(0.0063)
Birth place share of province population (in %) sq. ÷ 100	0.0510***	0.0570***	0.0440***
	(0.0036)	(0.0047)	(0.0030)
Percent of birth place population in province	0.0611***	0.0656***	0.0554***
	(0.0099)	(0.0107)	(0.0095)
Percent of birth place population in province sq. ÷ 100	-0.0086***	-0.0132***	-0.0026
	(0.0026)	(0.0030)	(0.0028)
Foreign-born share of province population (in %)	0.0508***	0.0692***	0.0425***
	(0.0088)	(0.0100)	(0.0078)
Foreign-born share of province population (in %) sq. ÷ 100	0.0471***	0.0500***	0.0455***
	(0.0081)	(0.0084)	(0.0082)
Labor market attribute			
Unemployment rate (in %)	-0.1211***	-0.1999***	-0.1108**
	(0.0282)	(0.0396)	(0.0444)
Population and distance			
Population size (log)	0.8366***	0.8415***	0.8201***
	(0.0565)	(0.0582)	(0.0670)
Distance from origin province (in 100 km)	-0.3759***	-0.3752***	-0.3878***
	(0.0641)	(0.0672)	(0.0630)
Distance from origin province (in 100 km) sq. ÷ 100	1.8780***	1.9580***	1.7793***
	(0.4585)	(0.4919)	(0.4350)
Non-migration dummy	33.6947***	32.0574***	31.6183***
	(0.5446)	(0.6600)	(0.4212)
Pseudo-R^2	0.9666	0.9559	0.9750
Number of individuals	794,171	344,828	449,343
Number of observations	53,209,457	23,103,476	30,105,981

Notes: The table presents coefficient estimates from fixed effects conditional logit. The estimation sample consists of 28-54-years-old male work migrants and non-migrants. We control for within-origin-province error correlation by implementing cluster robust variance estimator. Cluster robust standard errors are in parenthesis. All models also include province-group dummies, province of birth fixed effects, non-migration dummy, and dummy/dummies that accounts for the impact of province border change on migrants' location propensities. * significant at 10%; ** significant at 5%; ***significant at 1%.

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