EXCHANGE RATE PASS-THROUGH TO WAGES VIA INTERNATIONAL LABOR MOBILITY CHANNEL: EVIDENCE FROM TURKEY

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THE EXCHANGE RATE PASS-THROUGH TO WAGES VIA THE INTERNATIONAL WORKER MOBILITY CHANNEL: EVIDENCE FROM TURKEY

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ABSTRACT

THE EXCHANGE RATE PASS-THROUGH TO WAGES VIA THE INTERNATIONAL WORKER MOBILITY CHANNEL: EVIDENCE FROM TURKEY

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When researchers try to analyze the effect of ERPT on any given economy they are focusing on two different channels that ERPT can effect: Market power and the cost channel. In the cost channel, they focus heavily on the import price, the export price in which they may contain high import content, or on the consumer prices. Thus, in general, they do not account for the labor cost changes in such research designs. This is exactly the situation for the Turkish case. Our work, to our knowledge, will be the first study to analyze ERPT to wages. We use DID and UQR frameworks and we found that in case of depreciation in TL, wages increase in different degrees in different quantiles.

ÖZET

ULUSLARARASI İŞÇI HAREKETLILIĞI KANALI ÜZERINDEN DÖVIZ KURU GEÇIŞKENLILIĞININ ÜCRETLERE ETKISI: TÜRKIYE ÖRNEĞI

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Anahtar Kelimeler: Döviz Kuru Geçişkenliği, Maaş, Koşulsuz Nicel Regresyon, Yeniden Merkezlenmiş Etki Fonksiyonları, Çalışma Ekonomisi

Araştırmacılar Döviz Kuru Geçişkenliği'nin (DKG) herhangi bir ekonomi üzerindeki etkisini analiz etmeye çalıştıklarında, DKG'nin etkileyebileceği iki farklı kanala odaklanırlar: Pazar gücü ve maliyet kanalı. Maliyet kanalında ağırlıklı olarak ithalat fiyatlarına, yüksek ithalat içeriği içerebilecek ihracat fiyatlarına veya tüketici fiyatlarına odaklanırlar. Bu nedenle, genel olarak, bu tür araştırma tasarımlarında işgücü maliyeti değişikliklerini hesaba katmazlar. Türkiye örneğinde durum tam olarak budur. Çalışmamız, bildiğimiz kadarıyla, DKG'nin maaşlar üzerine analiz eden ilk çalışma olacaktır. Çalışmamızda DID ve UQR çerçevelerini kullandık ve Türk Lirası'nın değer kaybetmesi durumunda maaşların farklı maaş dağılım dilimlerinde, farklı oranlarda arttığını bulduk.

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To my wife
for her support
in this endless journey

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1. INTRODUCTION

Over the last decades globalization became the most prominent phenomenon and affected by it, immigration became a widespread practice around the world, especially in emerging markets. Since, migration decision is a result of a cost-benefit analysis on earnings (Massey et al. 1993; Sjaastad 1962; Stark and Bloom 1985), exchange rate fluctuations may increase the migration rates of the workers. In order to counter this labor supply decrease, and possible brain drain, domestic firms might be forced to increase the wages.

Turkey is in a period where the depreciation in the Turkish Lira (TL) continues nearly for a decade, starting roughly from 2014. We are trying to find the answer of the question above, whether there exists a relationship between exchange rate fluctuations and wages, by using this period of depreciation in Turkey. Specifically, we are trying to study this relationship on the workers, with highly mobile occupations, to see whether they experience an increase in their wages in case of a decrease in the value of TL.

In our analysis, we used Turkish Labor Force Survey (LFS) data. In order to create a variable for migration possibility difference between occupations, we combined Turkish LFS with the Database of Immigrants in OECD Countries (DIOC) of the OECD. Using this variable we created a Difference in Differences (DID) setup, and studied whether there exists an increase in the wages of workers with the high migration possibility. In order to deepen our analysis further, we used Quantile Regression, more specifically Unconditional Quantile Regression (UQR) which is structured upon Recentered Influence Functions (RIF) that is suggested by Firpo, Fortin, and Lemieux (2009) and further explained by Rios-Avila and Maroto (2020).

Using the Turkish LFS and DIOC data sets, we found that there exists a negative relationship between the value of Turkish Lira and wages of the Turkish workers. Our initial DID analysis on 1-Digit ISCO 08 codes shows that in case of 1 percentage point decrease in Real Effective Exchange Rate (REER) relative to the 2012-2014 average, it follows an increase in wages by 2.1%. UQR results suggest that this increase in wages realized in different ratios (betwen 1.1% and 3%) in different quantiles. When we control for the yearly fixed effects,[1] results showed that only the top-half of the distribution experienced an increase in wages. Thus, it can be said that this effect on wages is a special phenomenon for the workers with the higher wages.

In order to further examine the said effect, we restricted our analysis on the first three major groups' subgroups of the ISCO 08. In this setup, DID results suggest that in case of 1 percentage point decrease in REER relative to the 2012-2014 average,[2] wages increase by 0.5%. According to UQR results, wages increase by 27.8%, 34.6% and 12.2% for the $10th, 25th$ and $50th$ quantiles, the rest have negative coefficients. It seems that the decrease in the wages of the top-half of the distribution is a result of the fact that the occupations with the highest average wages have the lowest occupational mobility, that can be seen in the Figure 3.2.

We further expand our analysis for the sub samples of males and females. The results suggest that the increase in the wages of the males is significantly greater for DID setup and for every quantile in the analysis. This can be interpreted as the males having a higher immigration possibility, relative to the females.

In the literature the effect of exchange rates on wages is studied. There are works that try to connect exchange rate changes and fluctuations to workers' wages with different perspectives and for different countries. But, when researchers try to analyze the effect of ERPT on any given economy, they are focusing on two different channels that ERPT can effect: the market power and the cost channel. In the cost channel, they focus heavily on the import prices (Brun-Aguerre, Fuertes, and Phylaktis 2012; Campa and Goldberg 2005; Goldberg and Knetter 1996), the export prices in which they may contain high import content (Qian and Varangis 1994), or on the consumer prices. (Amoah and Aziakpono 2018; Campa and Goldberg 2008; Jimborean 2013; Parsley 2012) Thus, they do not account for the labor cost changes in such research designs. Some papers try to explain these changes via the integration of the source country to the international labor markets.(Mishra and Spilimbergo 2011)

There are also studies that try to connect exchange rate changes and fluctuations to prices of both labor and goods on various countries like Italy (Nucci and Pozzolo 2010), Taiwan (Chang 2010), sub-Saharan Africa (Abdulqadir and Chua 2020), or on

[1] In order to avoid multicollinearity between yearly fixed effects and REER we used interaction of REER with occupational mobility for our treatment variable.

[2] In order to make the interpretation easier for the UQR results we, first, assumed that occupational mobility takes the values of either 0 or 1. Then, we removed this assumption for a detailed analysis.

emerging markets. (Aleem and Lahiani 2014; Bussière, Delle Chiaie, and Peltonen 2014; Ca'Zorzi, Hahn, and Sánchez 2007) Our work will contribute to the ERPT literature by analyzing this effect via the international worker mobility channel.

Even though, as a developing country the Turkish case is interesting enough to be used as a highlighting example (Gopinath 2015), the relationship between exchange rates and wages has been neglected. The effect of ERPT on market integration (Ozturk 2020), and the cost channel were studied by various researchers, for the Turkish case. There exist studies which try to analyze the relation between ERPT and import prices (Türkcan 2005), export prices (Toraganli 2010), or both (Akgunduz et al. 2019; Tekin and Yazgan 2009; Ülke 2015). Yet, to our knowledge there is no such study that tries to describe the relation between exchange rates and labor costs or wages. Thus, my dissertation will be the first study for the Turkish case.

The second strand of literature that this work is connected to is on international migration. The reason why exchange rates have an effect on workers' wages is simple. It is because the depreciation in the source country's currency leads to an immigration of workers to the host countries, which then causes labor supply of the source country to fall. One can think that exchange rate changes as a proxy for economic well being of a country. In the literature, it is shown that a depreciation in the source country's currency increases the migration outflows from that country. (Gao 2015; Keita 2016) This effect is immediate when the source and host countries are neighbours or when the source country's integration to the international labor markets is high. (Hanson and Spilimbergo 1999). Also, exchange rate changes continue to effect immigrant workers on their return decision. (Yang 2006, 2008) Immigrant workers' decision to move abroad leads to a decrease in the source country's labor supply, and for some countries this outflow of workers is followed by an increase in the workers' wages in the source country. (Aydemir and Borjas 2007; Mishra 2007) Thus, our work will contribute to the international migration literature by connecting it with the ERPT literature, since exchange rate fluctuations may affect the migration decision.

The structure of my dissertation is as follows. First, we will briefly describe the background of Turkish labor markets with relation to the international worker migration in Section 2. Then, we will introduce our data sets in Section 3. In section 4, we will introduce our DID and UQR frameworks. And then, we will present our results in Section 5. Section 6 will conclude.

2. BACKGROUND

Immigration may be related to the labor market conditions of the host country (Bouton, Paul, and Tiongson 2011). If there exists a negative labor supply shock in the market, coherent with the theory, equilibrium wages increase. Thus, this stimulation induces emigrants to choose the host country as a result of maximizing their expected wages.

When we look at the Turkish immigrants' historical movements we see that there exist multiple periods of inflow and outflow of Turkish migrants. Starting from the 1950s, and until 1980s, Turkish migrants moved to Germany in order to seek a place in the job market. At first it was done only by the private initiatives of the people who wanted to migrate. However, after the coup in the 1960s in Turkey, immigration of Turkish citizens to Germany became the state policy to fight the economic crisis that was stemming from the depreciation of Turkish Lira (TL) and unemployment. Newly founded the State Planning Organization (SPO) published its first act for the planned migration of Turkish citizens to Germany. Remittances and the know-how transfer via the migrants, as well as the decrease in the unemployment in Turkey were the primary goals. Aside from the SPO, the coup government revised the constitution and made it possible for Turkish citizens to have the right to travel abroad. (İçduygu, Erder, and Gençkaya 2009)

Turkish citizens did not confine themselves to Germany, it was just the start.. After Germany, they migrated to other western European countries and when the said countries (and the European Union) put strict conditions and limitations for labor import, Turkish immigrants' new destination became Australia. (İçduygu, Erder, and Gençkaya 2009)

As we already showed the evidence for Turkish citizens' inclination and know-how to immigrate, we can conclude that there exist conditions which decrease the cost of immigration and increase the benefit. Apart from that, in the recent decades Turkish citizens' average education and foreign language knowledge have increased. This is a parameter that decreases the cost for integration to the host country's labor markets and society.

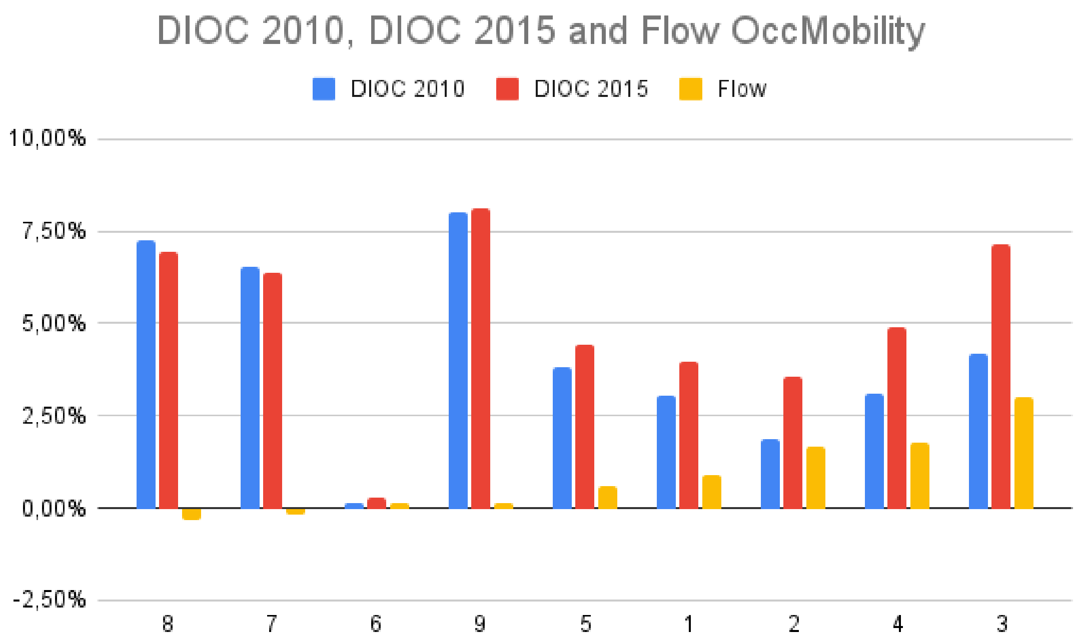
Thus, it can be said that for Turkish citizens, immigration for labor market opportunities is an old practice. This feature of Turkish citizens is coherent with the conditions and the results of the literature that analyzes the migration decision of workers. (Mishra and Spilimbergo 2011)

3. DATA

This study tries to analyze the ERPT to wages using the occupational worker mobility channel with the data on Turkish case. In order to construct our framework we employed two data sets.

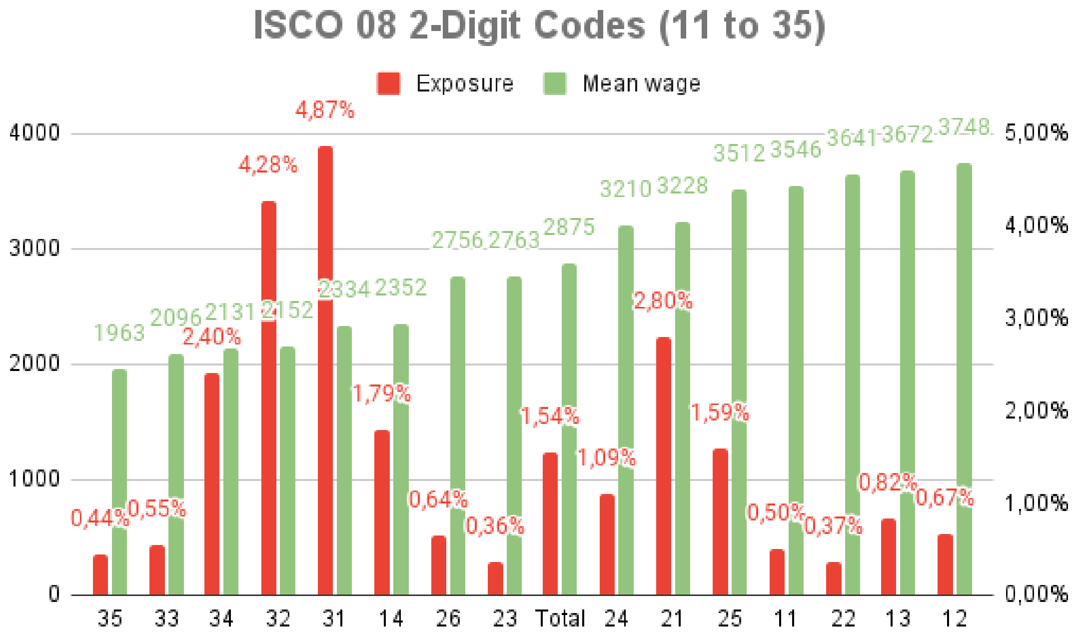
3.1 Database of Immigrants in OECD Countries (DIOC)

Figure 3.1 OccMobility, For ISCO08 Major ISCO codes



Note: Description of the ISCO 08 2-Digit Codes are as the following: 1 - Managers / 2 - Professionals / 3 - Technicians and Associate Professionals / 4 - Clerical Support Workers / 5 - Services and Sales Workers / 6 - Skilled Agricultural Forestry and Fishery Workers / 7 - Craft and Related Trades Workers / 8 - Plant and Machine Operators and Assemblers / 9 - Elementary Occupations

Figure 3.2 OccMobility and Mean Wages, For ISCO08 Major Codes of 1/2/3



Note: Description of the ISCO 08 2-Digit Codes are as the following: 11 - Chief executives, senior officials and legislators / 12 - Administrative and commercial managers / 13 - Production and specialised services managers / 14 - Hospitality, retail and other services managers / 21 - Science and engineering professionals / 22 - Health professionals / 23 - Teaching professionals / 24 - Business and administration professionals / 25 - Information and communications technology professionals / 26 - Legal, social and cultural professionals / 31 - Science and engineering associate professionals / 32 - Health associate professionals / 33 - Business and administration associate professionals / 34 - Legal, social, cultural and related associate professionals / 35 - Information and communications technicians /

In 2000, OECD compiled the population censuses across its members. In this data set, there were 34 host and more than 200 source countries on immigrants. This data set further compiled four rounds: DIOC 2000/2011, DIOC 2005/2006, DIOC 2010/2011, DIOC 2015/2016. They contain information on different themes and do not allow for cross tabulation analysis. However, among the variables there exists a few key variables that are crucial to our analysis. Namely, country of birth and occupation variables.

In order to conduct our main analysis we need occupational ISCO 08 codes at 2-Digit for each occupation. However, this kind of information is only given in the DIOC 2010/2011. The two rounds before 2010 contain occupation codes according to the ISCO 88. On the other hand DIOC 2015/2016 presents only the 1-Digit ISCO 08 codes. Thus, we will be using only the DIOC 2010/2011.

There are some problems with this selection of DIOC 2010/2011 which is a stock data set. As we described in the background section, Turkish immigrant workers in

OECD is not something new. Thus, in DIOC 2010/2011 workers who moved to an OECD member maybe decades ago will also be counted. This may contaminate our analysis. As we can see in the Figure 3.1, where we are comparing the three different data sets, stock data sets (DIOC 2010 and 2015) have significant drawbacks. As we pointed out before, this happens because of the previous immigration flows to OECD countries. When we look at the FlowOccMobility, which we constructed simply by taking the difference between DIOC 2015 and 2010, occupations with low skill requirement have even a negative rate of migration. Since there is no other option to create flow data for 2-Digit codes, we will be focusing on the first three major groups, and their sub groups, in our analysis.

In Figure 3.2 we provide the comparison between $OccMobility$, that we will be defining more clearly in the methodology section, and the average wages of occupations. It can be clearly seen that occupations with the highest average wages have some of the lowest $OccMobility$ measures. Thus, we are expecting to have an increase in wages in the bottom-half of the wage distribution, not the top-half. Since, top-half is constructed with the nearly managerial occupations and they have small $OccMobility$ measures.

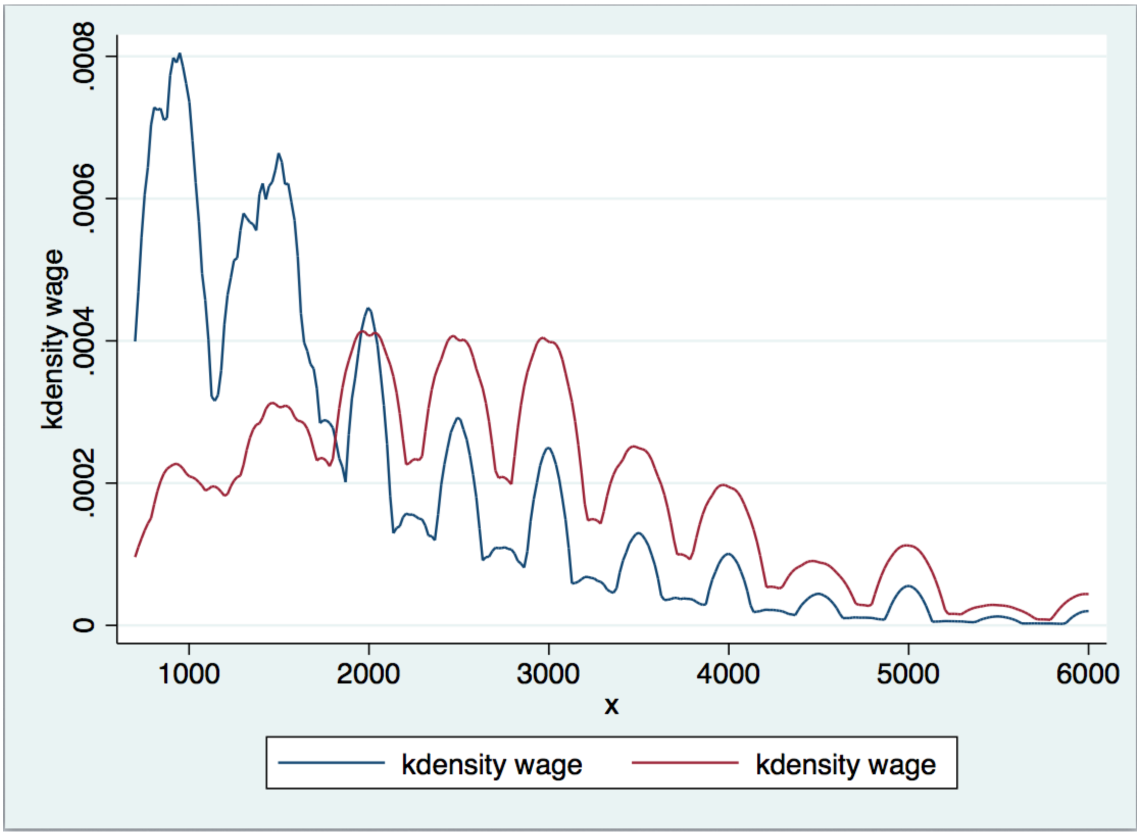
3.2 Turkish Labor Force Survey (LFS)

We will be using the Turkish LFS dataset through the span of 2012 and 2018. We have chosen this time frame because of several reasons. First, before 2012, LFS reports occupational codes in the form of ISCO 88. Secondly, starting from January 2018, according to the 8th article of the subsection of the act "Contracts in Foreign Currency and Indexed to Foreign Currency"[1], Turkish citizens cannot receive wages with a foreign currency or indexed to a foreign currency. Thus, this may create a disruption in the wages. Thirdly, this time period starts with a relative stability in Turkish Real Effective Exchange Rate (REER) through 2012 to 2014 and after 2014 it starts to decrease without an increase.

In table 3.2.1 we present summary statistics of the wages for the first three major groups of ISCO 08 2-Digit codes' subgroups. These measures are for the time period of 2012 and 2018. In LFS wages are reported as net monthly wages. In order to eliminate the mistyping in survey data we dropped the observations that are smaller

[1] https://www.resmigazete.gov.tr/eskiler/2018/11/20181116-8.htm

Figure 3.3 Kernel Density Wage Comparison



Note: In the table, x-axis is the net monthly wage of the workers. For this table, we restricted wages between 700 and 6000 in order for clarify the distinction of wage distribution of the first three major groups from the whole distribution. Red line is the wage distribution of the first three major groups of the ISCO 08.

than the 200 and greater than the 25000. For the upper end, only a couple of observations were in the data set, it was less than 10 observations for for the whole time period.

Other than the mean wages, we also reported the standard deviations of each occupational group with their respective percentile. Summary statistics imply interesting features since subgroups of major group 1, approximately, has the highest standard deviations. When we compare this information with the Figure 3.3, where we compare OccMobility with the Mean Wages, it further enhances the point that managerial positions' distinct feature on their wages. Even though they have the highest average wages, they have the lowest OccMobility rates. Furthermore, their dispersion of in group wages is higher than the other occupational groups. This feature of the managerial occupations will be important in our analysis when we will interpret the results.

Table 3.2.1 Summary Statistics

	Educ		Sex		Age		RFM		Wage	
ISCO	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
1	0,76	0,43	0,82	0,38	42,27	10,1	0,07	0,09	3469,89	2877,35
2	0,94	0,23	0,53	0,5	36,71	9,46	0,14	0,16	3008,82	1634,33
3	0,6	0,49	0,73	0,45	35,39	9,98	0,24	0,29	2150,42	1785,8
4	0,56	0,5	0,59	0,49	35,18	10,17	0,14	0,17	1800,36	895,73
5	0,24	0,43	0,67	0,47	35,75	11,85	0,05	0,06	1390,38	848,07
6	0,04	0,2	0,89	0,31	39,91	12,53	0,01	0,01	1140,83	574,42
7	0,11	0,31	0,92	0,27	34,44	10,8	-0,01	0,02	1376,5	680,15
8	0,1	0,3	0,89	0,31	37,55	10,42	-0,03	0,03	1441,92	673,44
9	0,07	0,26	0,71	0,46	36,52	11,39	0,01	0,01	1193,16	555,55
Total	0,36	0,48	0,72	0,45	36,26	10,89	0,06	0,14	1789	1369,8

	Educ		Sex		Age		RM		Wage	
ISCO	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
11	0,56	0,5	0,9	0,3	47,26	10,93	0,04	0,05	3459,72	4226,78
12	0,86	0,34	0,75	0,43	41,14	9,05	0,05	0,06	3755,94	2365,45
13	0,91	0,29	0,84	0,37	41,68	9,01	0,07	0,08	3669,98	2173,31
14	0,55	0,5	0,8	0,4	36,69	9,14	0,14	0,17	2331,98	1750,07
21	0,97	0,16	0,7	0,46	35,26	9,89	0,23	0,27	3211,04	1700,5
22	0,92	0,27	0,33	0,47	37,15	9,87	0,03	0,04	3612,8	2343,04
23	0,99	0,11	0,44	0,5	37,32	9,43	0,03	0,03	2739,89	1206,54
24	0,88	0,32	0,78	0,41	35,34	8,06	0,09	0,11	3202,59	1480,83
25	0,98	0,15	0,8	0,4	31,83	6,63	0,13	0,16	3508,04	2250,58
26	0,81	0,4	0,67	0,47	37,73	10,09	0,05	0,06	2659,94	1599,66
31	0,56	0,5	0,91	0,28	37,13	9,85	0,4	0,48	2350,07	2012,16
32	0,65	0,48	0,47	0,5	32,67	10,21	0,35	0,42	2046,18	1060,26
33	0,62	0,48	0,65	0,48	35,65	9,62	0,04	0,05	2059,28	1190,44
34	0,58	0,49	0,71	0,46	34,15	10,33	0,2	0,24	2090,02	3088,57
35	0,6	0,49	0,86	0,35	32,07	9,09	0,03	0,04	1877,03	1056,8
Total	0,82	0,39	0,64	0,48	37,26	9,99	0,11	0,23	2843,86	1990,92

Note:Description of the ISCO 08 Codes are as the following: **1-Digit** 1 - Managers / 2 - Professionals / 3 - Technicians and Associate Professionals / 4 - Clerical Support Workers / 5 - Services and Sales Workers / 6 - Skilled Agricultural Forestry and Fishery Workers / 7 - Craft and Related Trades Workers / 8 - Plant and Machine Operators and Assemblers / 9 - Elementary Occupations **2-Digit** 11 - Chief executives, senior officials and legislators / 12 - Administrative and commercial managers / 13 - Production and specialised services managers / 14 - Hospitality, retail and other services managers / 21 - Science and engineering professionals / 22 - Health professionals / 23 - Teaching professionals / 24 - Business and administration professionals / 25 - Information and communications technology professionals / 26 - Legal, social and cultural professionals / 31 - Science and engineering associate professionals / 32 - Health associate professionals / 33 - Business and administration associate professionals / 34 - Legal, social, cultural and related associate professionals / 35 - Information and communications technicians

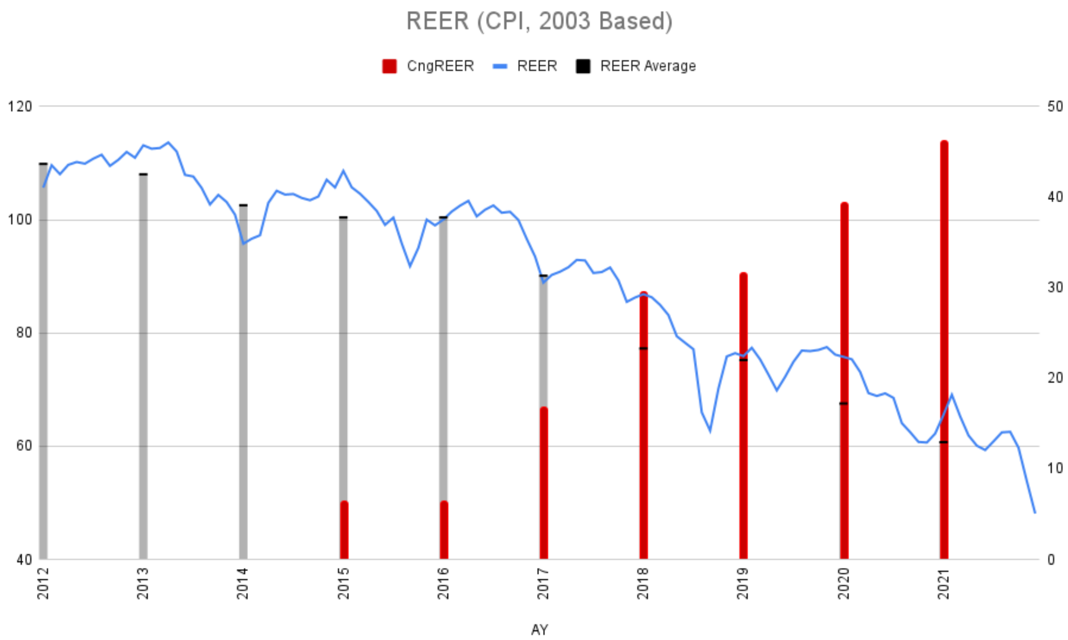
In Figure 3.2, we are presenting the kernel density wage comparison between the whole wage distribution and the wage distribution of only the first three major groups of the ISCO 08. It can be clearly seen that, first three major groups have higher density rates than the whole distribution. This fact states that, they have higher net monthly wages than the other major groups. Thus, it is a supporting evidence for us to choose only the first three major groups rather than examining the whole distribution. As we stated above, because of the nature of the DIOC data sets, we cannot employ a flow type data. When we try to work with stock data and the whole major groups, our analysis will be misguided.

3.3 Real Effective Exchange Rate (REER) Data

REER data is from the Central Bank of Republic of Turkey (CBRT) which publishes different datasets on REER. The type we use is REER based on the CPI prices. This data can be found in the official website of the CBRT. We have computed the average REER by year, from the CBRT monthly REER data from 2012 to 2018.

As one can see in Figure 3.4, annual average REER of the years 2012, 2013 and 2014 are somewhat in similar. The difference between them is not steep. Even though, in the second half of the 2014 REER fell under the 100, on average, annually it did not perform in the same fashion. Red lines in the figure stand for the percentage change of the REER of year t with respect to annual REER average of the period of 2012 and 2014. It can be clearly seen that CngREER keeps increasing year by year after 2015.

Figure 3.4 Percentage Change in REER



Note: REER data is drawn by monthly data. CngREER is the relative percentage change in REER of year t with respect to the REER average of the period starting from 2012 to 2014. Left axis: REER Average and REER; Right axis: CngREER.

4. METHODOLOGY

In the analysis of the ERPT to wages via occupational mobility, we will use two different regression methods: Difference in Differences (DID) and Unconditional Quantile Regression (UQR).

4.1 Difference in Difference (DID)

Using the 2012-2014 period as control groups, we created a treatment variable that is in parallel with the standard DID setups. Our initial equation is the following:

$$ln(wage_k) = \beta_0 + \beta_1 Educ_k + \beta_2 Age_k + \beta_3 Age_k^2 + \beta_4 ReerMobility_k + \beta_5 Sex_k + \epsilon_k \tag{4.1}$$

Where *Educ* is a dummy variable which takes the value of 0 if the individual i's education level is less than university level, it takes the value of 1 if it is at the university or higher level. Also, *Sex* is a dummy variable which takes the value of 0 if the individual i is female and it takes the value of 1 if male. The main variable in our analysis $ReerMobility$ is an interaction term:

$$ReerMobility = (CngREER)x(OccMobility) \tag{4.2}$$

REER adjusted for CPI data comes from the CBRT and $CngREER$ is calculated by the following procedure:

$$CngREER = (1 - \frac{REER\,of\,year\,T}{Average\,of\,REER\,between\,2012\,and\,2014}) * 100 \tag{4.3}$$

where $T = 2015,\ 2016,\ 2017\ and\ 2018$. Thus $CngREER$ can be interpreted as the percentage point change in REER at year T relative to the average of REER between 2012 and 2014. Since, after the 2014 REER decreases monotonically, one should interpret this variable as “a decrease in REER by B percentage points in year T relative to the average of REER between 2012 and 2014”. Or simply percentage point decrease of REER in year T. The other variable of the interaction term, $OccMobility$, refers to occupational mobility. Which is a proxy for international worker mobility for Turkish workers with the occupation j. For our main analysis, which focuses to the first three ISCO 08 codes major groups (from 11 to 35), $OccMobility$ calculated as follows:

$$OccMobility = \frac{Number\ of\ Turkish\ workers\ with\ occupation\ j\ in\ the\ OECD\ countries\ in\ 2010}{Number\ of\ workers\ with\ occupation\ j\ in\ Turkey\ in\ 2012} \tag{4.4}$$

We chose the denominator to be from the LFS 2012 because this is the earliest year in our data set that we can create our variable without any other disruptions. Secondly, even when we compared this variable with the variable that is created using the average of LFS occupations, the difference between them was substantial.

Yet, this is a stock variable. Since there is no data for the ISCO 08 2-digit codes in the DIOC 2015/2016, one cannot create a flow variable. Instead, using the ISCO 08 1-digit codes from DIOC 2010/2011 and DIOC 2015/2016 one can create a flow variable, namely, $FlowOccMobility$ with the following procedure:

$$FlowOccMobility = \frac{DIOC_{2015}^{j} - DIOC_{2010}^{j}}{Number\ of\ workers\ with\ occupation\ j\ in\ Turkey\ in\ 2012} \tag{4.5}$$

where $DIOC_{2015}^{j}$ ($DIOC_{2010}^{j}$) stands for the number of Turkish workers with occupation j in the OECD countries in 2015 (2010).

Because of the nature of $CngREER$, $OccMobility$ and $FlowOccMobility$ we cannot add year and ISCO 08 codes as control variables. Because, year and the REER would create multicollinearity. Similar problem occurs between ISCO 08 and $OccMobility$, and, ISCO 08 and $FlowOccMobility$. Instead, what we can do is to employ control variables as interaction terms with year. In order to solve the multicollinearity issue between ISCO 08 and $OccMobility$ we employ our treatment variable as an interaction term with $OccMobility$ and REER. This interaction term is in parallel lines with the treatement variable of the standard DID models. In the equation

(4.1), we are controlling for yearly regional fixed effects, yearly sectoral fixed effects and occupational fixed effects (ISCO 08 codes).

4.2 Unconditional Quantile Regression (UQR)

After Firpo, Fortin, and Lemieux (2009) published their work, Recentered Influence Functions (RIF) gained attention in the literature. They extended their ideas with a couple of publications. Firpo, Fortin, and Lemieux (2018) broadened the use of RIF regressions. Further, their three step procedure was further simplified by Rios-Avila (2020) and the difference between Linear Regression, Unconditional Quantile Regression (UQR), Conditional Quantile Regression (CQR), and Quantile Treatment Effect (QTE) clearly explained by Rios-Avila and Maroto (2020). In this paper, we will use the UQR methodology that is suggested by Rios-Avila (2020) in the spirit of Firpo, Fortin, and Lemieux (2009).

In order to understand the UQR based on RIF Regressions, first we must examine the underlying Influence Functions (IF). The intuition behind the IF can be explained via a thought experiment given in the Rios-Avila and Maroto (2020). Assume that there exists a sample in the beginning and a new observation added to that sample. Let v be the any statistic of interest that is a function of the cumulative distribution function, and v_0 and v_1 be the denotations for the sample size N and N+1, respectively. The change caused on v by adding a new observation to the sample, is simply the difference between v_0 and v_1. An IF of an observation is a function that rescales this difference by the relative change in the sample size. This expression is also called as a Gateaux derivative and the intuition behind that, it is the first order (linear) approximation of the influence of an observation on the distribution v.[1]

The RIF, suggested by Firpo, Fortin, and Lemieux (2009), complements the IF by adding the the v of the original distribution to the IF of the observation.

$$RIF(y_i, v, F_y) = v(F_y) + IF(y_i, v, F_y) \tag{4.6}$$

[1] The exact mathematical expressions behind this intuition can be found in Rios-Avila and Maroto (2020), and Rios-Avila (2020).

Where F_y is the cumulative distribution of the original sample, y_i is the outcome of an observation (let say, earnings). As Rios-Avila (2020) suggests, this expression can be interpreted as the relative contribution of an observation the creation of the distribution of that sample. Since we can recover the underlying distributional statistic via the sample averages. Rios-Avila and Maroto (2020)

In order to estimate UQR via RIF first one needs to estimate the RIFs for each observation, then, using these RIFs for each observation in the place of dependent variable, regress other independent variables. (Rios-Avila 2020) In the end, our model that we defined in the DID section becomes:

$$RIF(y_i, Q_\tau(.), F_y) = \beta_0 + \beta_1(\tau) ReerOccMob_{it} + \beta_2(\tau) Z_{it} + \beta_3(\tau)\delta_{it} + \epsilon_{it} \tag{4.7}$$

where $RIF(y_i, Q_\tau(.), F_y)$ is the RIF that is obtained after calculating the IFs of the observations and then adding the $Q_\tau(.)$, Z_{it} is the other explanatory variables $(sex, age, education$, and δ_{it} is the controlled fixed effects (sectoral, regional and occupational).

UQR design fits to our question because of the fact that UQR can answer the following: How much would the observed distribution of workers' earnings (across individuals and time) change, measured by the change in the τ^{th} quantile, if all occupations had, on average, a 1 percentage point decrease in REER, holding everything else constant? The method allows for fixed effects to be implemented in the regression.(Rios-Avila 2020) We can answer this question with Unconditional Partial Effect (UPE) (Firpo, Fortin, and Lemieux 2009; Rios-Avila 2020) by simply differentiating observed quantile and the estimated quantile:

$$\begin{aligned} \hat{Q}'_\tau(y) = & \\ &= E(RIF'(y_i, Q_\tau(.), F_y)) \\ &= E(\beta_0 + \beta_1(\tau)[ReerOccMob_{it} + \Delta ReerOccMob] + \beta_2(\tau) Z_{it} + \beta_3(\tau)\delta_{it} + \epsilon_{it}) \\ &= E(\beta_0 + \beta_1(\tau)[ReerOccMob_{it}] + \beta_2(\tau) Z_{it} + \beta_3(\tau)\delta_{it} + \epsilon_{it}) + E[\beta_1(\tau)\Delta ReerOccMob] \\ &= Q_\tau(y) + \beta_1(\tau)\Delta\overline{ReerOccMob} \end{aligned} \tag{4.8}$$

$$\hat{Q}'_\tau(y) - Q_\tau(y) = \beta_1(\tau)\Delta\overline{ReerOccMob} \tag{4.9}$$

5. RESULTS

Because of the unavailability of the flow data for ISCO 08 2-digit codes, we will first conduct our analysis on ISCO 08 1-digit codes. This analysis may contain bias, because of the nature of 1-Digit codes and the relation of them with the exposure variable that we defined above. Thus, for the analysis with the 1-Digit Codes we will not use $ReerMobility$ instead we will only use $CngREER$. Nevertheless, it will guide our analysis for better interpretations.

5.1 Results on ISCO 08 1-Digit Codes

DIOC has two rounds that contains ISCO 08 1-Digit codes: 2010/2011 and 2015/2016. Using these two rounds we can create $FlowOccMobility$ for ISCO 08 1-Digit. (Equation 4.5) However, when we aggregate occupations for their major group, occupational mobility becomes less precise because of the fact that real variation comes from the sub groups of 1-Digit Codes. For instance, major group 1 (Managers) has $0,92\,\%$ for its $OccMobility$ however its sub-groups have $0,50\,\%$ (11-Chief executives, senior officials, and legislators), $0,67\,\%$ (12-Administrative and commercial managers), $0,82\,\%$ (13-Production, and specialised services managers), $1,79\,\%$ (14-Hospitality retail and other services managers), respectively. This is valid for every case on the ISCO 08 codes.

We are controlling for sectoral fixed effects, regional fixed effects, and occupational fixed effects. Also, for wages, we are restricting our analysis on wages between 700 TL and 25.000 TL, both included. We are employing this strategy in order to manage the errors stemming from the nature of the survey data, like mistyping or wrong reporting. Lower end of the restriction selected as 700 because of the fact that 2012 real minimum wage was 740TL. Upper end selected as 25.000 TL [1] Results have shown in Figure 5.1. First model of the regression results, stands for the DID regression. Whereas, other models stands for UQR with their respective quantiles as the interested statistic.

Table 5.1.1 Regression Results for 1-Digit Codes

	DID	UQR				
	lwage	Q(10)	Q(25)	Q(50)	Q(75)	Q(90)
Education	0.135***	-0.059***	0.004***	0.089***	0.355***	0.387***
Robust	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)
Bootstrap	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)	(0.005)
Age	0.035***	0.024***	0.023***	0.033***	0.053***	0.031***
Robust	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Bootstrap	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***
Robust	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bootstrap	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex	0.131***	0.058***	0.073***	0.109***	0.227***	0.192***
Robust	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.004)
Bootstrap	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.004)
CngREER	0.021***	0.011***	0.014***	0.019***	0.027***	0.030***
Robust	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bootstrap	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.336***	6.144***	6.347***	6.422***	6.080***	6.841***
Robust	(0.005)	(0.008)	(0.006)	(0.005)	(0.012)	(0.012)
Bootstrap	(0.005)	(0.008)	(0.006)	(0.006)	(0.014)	(0.016)
Observations	625189	625189	625189	625189	625189	625189
R^2	0.594	0.130	0.241	0.415	0.444	0.302

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors and Bootstrap standard errors are in parentheses. Bootstrap standard errors calculated over 200 repetitions with the seed 101. For all models, we are controlling for sectoral, regional, and occupational fixed effects.

In Figure 5.1.1. DID results suggest that in case of a 1 percentage point decrease in REER, or 1 point increase in $CngREER$, wages increase by 2.1%. Whereas, UQR results show the effect of such depreciation on the quantiles. However, interpretation of UQR results is a bit tricky. Yet, our model fits the description of this

[1] We have estimated the same model without any restrictions. In general, the difference between results are minuscule to a level where it does not change the general interpretation of results.

interpretation perfectly. Since, REER changes for all of the occupations at the same rate.

In order to interpret the results in a clear format, first, assume that $OccMobility$ takes only the values of 0 and 1. Then, if the average REER was to decrease by one, we would expect wages at the bottom of the distribution (10^{th} quantile) to increase by 1.1%, and 3% at the top of the distribution (90^{th} quantile). However, this results might be misleading because of the problem described above and the fact that minimum wages in Turkey increased almost annually, which can effect the lower end of the distribution. It is also interesting that (90^{th}) and (75^{th} quantiles) coefficients are approximately two times of the other quantiles. Figure 5.2 shows the occupational mobility for 1-Digit codes. DIOC 2010 works same as the Equation 4.4, but for DIOC 2015 we are using the 2015 data. Flow is simply the difference between these two.

In the Figure 3.1 problems of the stock type data can be clearly seen. Turkish immigrant residents in the OECD countries that moved to host countries long ago, determines the $OccMobility$ levels. If we take in to account DIOC 2010, occupations with the low-skill requirements (ISCO08 codes of 6, 7, 8, 9) would be seemed as having higher mobility levels. However, when we look at the $FlowOccMobility$, it is clear that occupations with high skill requirements (ISCO08 codes of 1, 2, 3, 4, 5,) actually have higher mobility levels.

In order to understand the role of the occupational mobility more clearly, we conducted the same regression as the previous model but this time we interacted the $FlowOccMobility$ with the $CngReer$ in order to create $ReerFlowMob$ as in the same lines with the $ReerMobility$. Figure 5.1.2 shows the regression results. According to results, depreciation in the Turkish Lira increases wages only at the top of the distribution (75^{th} and 90^{th}quantiles). Which implies that this phenomenon is related with the occupations with the high-skilled requirements.[2] Thus, for our analysis we will focus on the occupations with high skill requirements.

[2]Yet, UQR-RIF Regression results are hard to interpret. Since this table is not our main goal in this paper, we will not interpret them with more precise options. However, even then it is clear that our interpretation is indeed viable.

Table 5.1.2 Regression Results for 1-Digit Codes, Year Interaction FE

	DID	UQR				
	lwage	Q(10)	Q(25)	Q(50)	Q(75)	Q(90)
Education	0.266***	0.143***	0.124***	0.155***	0.492***	0.406***
Robust	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.004)
Bootstrap	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)
Age	0.059***	0.069***	0.043***	0.039***	0.057***	0.025***
Robust	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Bootstrap	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Age^2	-0.001***	-0.001***	-0.001***	-0.000***	-0.001***	-0.000***
Robust	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bootstrap	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex	0.165***	0.115***	0.111***	0.124***	0.251***	0.171***
Robust	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Bootstrap	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
ReerFlowMob	-0.034***	-0.219***	-0.381***	-0.322***	0.677***	1.031***
Robust	(0.006)	(0.006)	(0.005)	(0.006)	(0.019)	(0.019)
Bootstrap	(0.006)	(0.006)	(0.005)	(0.006)	(0.020)	(0.021)
Constant	5.912***	5.184***	5.972***	6.414***	6.091***	7.150***
Robust	(0.006)	(0.011)	(0.006)	(0.005)	(0.010)	(0.009)
Bootstrap	(0.006)	(0.013)	(0.008)	(0.006)	(0.013)	(0.010)
Observations	670935	670935	670935	670935	670935	670935
R^2	0.618	0.259	0.415	0.481	0.497	0.392

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors and Bootstrap standard errors are in parentheses. Bootstrap standard errors calculated over 200 repetitions with the seed 101. For all models, we are controlling for annual sectoral and annual regional fixed effects with interaction terms and we also control for occupational fixed effects via controlling for ISCO 08 1-Digit codes.

5.2 Results on ISCO 08 2-Digit Codes

The results at the previous subsection suggest that there is a positive (negative) relationship between the $ReerMobility$ and the wages at the top-half (bottom-half) of the distribution. This is indeed a clear indication that without the presence of the flow type data such analysis will be open to extreme bias that stems from the nature of $OccMobility$. The reason is that stock mobility variables include workers with low-skill required jobs like cleaning that moved to OECD countries decades ago. Since we do not have flow data for ISCO 08 2-digit codes, we will restrict our analysis on the first three major sub groups (from 11 to 35, both included).

Before we start to interpret the regression results that is reported in Figure 5.2.1, first assume that $OccMobility$ only takes two values, 0 and 1.[3] DID results in the Figure 5.2.1. (Model 1) indicate that 1% point increase in $ReerMobility$ leads to 5.6% increase in wages. This can be translated as: 1% point decrease in REER relative to the 2012:2014 (1% point increase in $ReerMobility$) period, leads to an increase in wages by 5.6%. Thus, it is clear that there exists a positive (negative) relationship between $ReerMobility$ (REER) and wages.

However, UQR results indicate an interesting result, that is, at the top of the distribution of wages positive relationship between $ReerMobility$ and wages disappears, instead, it turns to a negative relationship where an increase in $ReerMobility$ (which is a decrease in the value of TL, or 1% increase in $ReerMobility$, leads to an decrease in wages. Even though it is not significant for the 75th quantile. 1% point increase in $ReerMobility$ (which can be translated as a decrease in the value of TL) leads to a decrease by 27.3% in wages in the 90th quantile.

This may seem contrary to our hypothesis which is to claim that occupations with a high level of $OccMobility$ variable would have higher wages thus, in case of a decrease in the value of TL the increase in wages would be higher. However, when one looks at the Figure 3.2 one would see that occupations with the lowest exposure variable, in general, have the highest average wages. Only the ISCO08 2-Digit codes of 21 (Science and engineering professionals) and 25 (Information and communications technology professionals) have higher mobility levels than the total average. Thus, the negative relationship between $ReerMobility$ and wages at the 75^{th} and 90^{th} quantiles does not falsify our analysis. Instead, they support our claim.

[3]This assumption is needed in the begging. Otherwise interpretation of this interaction term would be hard for reader to understand. Later, we will remove this assumption.

Table 5.2.1 Regression Results for 2-Digit Codes

	DID	UQR				
	lwage	Q(10)	Q(25)	Q(50)	Q(75)	Q(90)
Sex	0.140***	0.143***	0.158***	0.101***	0.137***	0.205***
Robust	(0.002)	(0.006)	(0.004)	(0.002)	(0.003)	(0.005)
Bootstrap	(0.002)	(0.007)	(0.005)	(0.002)	(0.003)	(0.006)
Age	0.070***	0.133***	0.127***	0.056***	0.045***	0.046***
Robust	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Bootstrap	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
Robust	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bootstrap	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.296***	0.373***	0.424***	0.233***	0.251***	0.322***
Robust	(0.003)	(0.010)	(0.007)	(0.003)	(0.004)	(0.006)
Bootstrap	(0.003)	(0.012)	(0.008)	(0.003)	(0.004)	(0.006)
ReerMobility	0.056***	0.278***	0.346***	0.122***	-0.001	-0.273***
Robust	(0.008)	(0.020)	(0.016)	(0.008)	(0.011)	(0.019)
Bootstrap	(0.008)	(0.019)	(0.016)	(0.008)	(0.010)	(0.021)
Constant	5.982***	3.994***	4.380***	6.408***	6.891***	7.002***
Robust	(0.017)	(0.050)	(0.031)	(0.014)	(0.016)	(0.028)
Bootstrap	(0.017)	(0.063)	(0.044)	(0.016)	(0.018)	(0.033)
Observations	174141	174141	174141	174141	174141	174141
R^2	0.480	0.236	0.337	0.403	0.339	0.199

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors and Bootstrap standard errors are in parentheses. Bootstrap standard errors calculated over 200 repetitions with the seed 101. For all models, we are controlling for annual sectoral and annual regional fixed effects with interaction terms and we also control for occupational fixed effects via controlling for ISCO 08 2-Digit codes.

In the UQR-RIF regressions we cannot interpret the results by directly increasing the $OccMobility$ by 1% point because UQR accounts for the small location shifts and the highest $OccMobility$ is approximately 5%. Thus one percentage point increase in $OccMobility$ does not reflect a small location shift in $ReerMobility$. Additionally, in the UQR we have to be interpreting the results in the case of an increase for all of the population that is: an increase in the average $OccMobility$ in the population by 1%. This is an even greater location shift. Since, our nominator in the calculation of $OccMobility$ is only for the 2010, it is not optimal to focus on the $OccMobility$ changes. Rather, focusing on REER changes would give us healthier interpretations.

Now, we will remove our assumption on $OccMobility$ that we assume previously, since it is not logical to divide occupations with 100% and 0% mobility rates. Instead, for the sake of interpreting the UQR, assume that average $OccMobility$ in the population is only 5%. $ReerMobility$ for 10^{th} quantile is 27.8%. In order to see the increase in wages by 27.8%, $CngREER$ should increase by 20% points. Then we can say that, when there is a 20% point decrease in REER relative to the average of 2012 and 2014 period, wages increase by 27.8%, 34.6%, and 12.2% at the 10^{th}, 25^{th}, and 50^{th}, respectively. Similarly, the decrease in wages at the 90^{th} quantile would be 27.3%.

5.2.1 Different Sex Groups

In this sub section, we will try to analyze the said effects of the exchange rate fluctuations via the occupational mobility for the two sub samples: male and female. We will be analyzing two different sub samples separately for the sake of easier interpretation. If we try to analyze the effect trough a dummy variable the interpretation for this dummy variable should be like the following: "If the average number of males in the population increased by 1, what would happen to the wage at the $(.)^{th}$ quantile." Such analysis will restrict our interpretation. Thus, in this subsection we will focus on the sub samples of males and females separately.

Table 5.2.2 Regression Results for Sub sample of Males

	DID	UQR				
	lwage	Q(10)	Q(25)	Q(50)	Q(75)	Q(90)
Age	0.086***	0.174***	0.137***	0.059***	0.051***	0.049***
Robust	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Bootstrap	(0.001)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Age^2	-0.001***	-0.002***	-0.001***	-0.001***	-0.001***	-0.000***
Robust	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bootstrap	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.350***	0.536***	0.478***	0.249***	0.269***	0.265***
Robust	(0.004)	(0.013)	(0.008)	(0.004)	(0.004)	(0.006)
Bootstrap	(0.004)	(0.016)	(0.010)	(0.005)	(0.005)	(0.006)
ReerMobility	0.012	0.173***	0.403***	0.157***	0.014	-0.301***
Robust	(0.010)	(0.027)	(0.020)	(0.010)	(0.014)	(0.019)
Bootstrap	(0.010)	(0.026)	(0.020)	(0.014)	(0.014)	(0.019)
Constant	5.720***	3.071***	4.223***	6.408***	6.887***	7.259***
Robust	(0.022)	(0.069)	(0.038)	(0.017)	(0.020)	(0.027)
Bootstrap	(0.022)	(0.095)	(0.049)	(0.020)	(0.022)	(0.030)
Observations	112760	112760	112760	112760	112760	112760
R^2	0.493	0.277	0.365	0.412	0.365	0.234

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors and Bootstrap standard errors are in parentheses. Bootstrap standard errors calculated over 200 repetitions with the seed 101. For all models, we are controlling for annual sectoral and annual regional fixed effects with interaction terms and we also control for occupational fixed effects via controlling for ISCO 08 1-Digit codes.

In the sub sample of males (Figure 5.2.2), the effect of $ReerMobility$ seems to be highest at the 25^{th} quantile with 40.3%, and the effect of Age seems to be decreasing for each quantile. The effect of $ReerMobility$ on log wages are positive except for the 90^{th} quantile where it is negative. Also, at the 75^{th} quantile the effect of $ReerMobility$ is insignificant. In the sub sample of females (Figure 5.2.3.), the effect of $ReerMobility$ is grater at the 25^{th}quantile with 24.8%.

Table 5.2.3 Regression Results for Subsample of Females

	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.089***	0.146***	0.127***	0.058***	0.033***	0.018***
Robust	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)
Bootstrap	(0.002)	(0.005)	(0.006)	(0.002)	(0.001)	(0.002)
Age^2	-0.001***	-0.002***	-0.001***	-0.001***	-0.000***	-0.000***
Robust	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bootstrap	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.384***	0.482***	0.449***	0.269***	0.197***	0.183***
Robust	(0.007)	(0.019)	(0.013)	(0.006)	(0.006)	(0.007)
Bootstrap	(0.007)	(0.021)	(0.021)	(0.010)	(0.006)	(0.008)
ReerMobility	0.001	0.082**	0.248***	0.012	-0.106***	-0.104***
Robust	(0.016)	(0.034)	(0.025)	(0.016)	(0.018)	(0.026)
Bootstrap	(0.016)	(0.036)	(0.037)	(0.016)	(0.019)	(0.028)
Constant	5.531***	3.706***	4.454***	6.352***	7.156***	7.685***
Robust	(0.043)	(0.080)	(0.053)	(0.026)	(0.026)	(0.034)
Bootstrap	(0.043)	(0.093)	(0.134)	(0.049)	(0.025)	(0.032)
Observations	64755	64755	64755	64755	64755	64755
R^2	0.493	0.222	0.350	0.422	0.352	0.231

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors and Bootstrap standard errors are in parentheses. Bootstrap standard errors calculated over 200 repetitions with the seed 101. For all models, we are controlling for annual sectoral and annual regional fixed effects with interaction terms and we also control for occupational fixed effects via controlling for ISCO 08 1-Digit codes.

When we compare the DID results for male (1.2%) and female (0.1%) sub samples, it is clear that the effect of $ReerMobility$ is greater for the males, whereas on females it is not significant. However, at the 90^{th} quantile the negative effect is greater for males. This is again related to the Figure 3.2 where we compare the mean wages and $OccMobility$. For the managerial occupations (ISCO 08 major code of 1) number of observations for males is 24.172 whereas for females it is only 5.321. These occupations have the highest averages wages but lowest mobility measures. Thus, since males have higher number of observations in this category, it is intuitive to accept that they have the highest negative effect on the 90^{th} quantile.

For every model we employ in our analysis the effect of $ReerMobility$ is greater for males compared to females. This can be interpreted as (since we are controlling for the sectoral yearly fixed effects, yearly regional effects and occupational fixed effects) females having smaller occupational mobility occupations (i.e. they are less mobile) than men. It is also compatible with the summary statistics we presented before.

6. CONCLUSION

Using DIOC data set over the Turkish LFS (through the 2012 and 2018 period) to calculate occupational mobility, we analyzed the effect of ERPT to wages via the occupational mobility channel with the DID and UQR models. Our initial analysis, without the yearly fixed effects, with DID framework on ISCO08 1-Digit Codes, shows that mobility effect at 1 percentage point decrease in REER, or 1 point increase in $CngREER$, leads to an increase in wages by 2.1%. Additionally, UQR results suggest that if the average REER was to decrease by 1 percentage point, we would expect wages at the bottom of the distribution ($10th$ quantile) to increase by 1.1%, and 3% at the top of the distribution ($90th$ quantile). Because we did not control for year fixed effects, results are confounded. However, when we account for the year fixed effects, we have to interact the $CngREER$ with the $OccMobility$ to create $ReerMobility$. This new regression suggests that the relation between $ReerMobility$ and wages are negative (positive) at the top-half (bottom-half) of the distribution. Thus, we can say that the negative relation between $CngREER$ (change in REER) and wages is a phenomenon for the occupations with the higher average wages.

When we estimate the same frameworks over the ISCO08 2-Digit codes first three major groups (1, 2, 3), if we assume $OccMobility$ has the values of 0 or 1, mobility effect at 1% point increase in $CngREER$ (1% point decrease in REER relative to the 2012:2014 period), leads to an increase in wages by 2.1%, in the DID model.

Whereas according to the UQR results mobility effect at 1% point increase in $ReerMobility$ (which can be translated as a decrease in the value of TL) leads to an increase in wages by 27.8%, 34.6%, and 12.2% for the $10th$, $25th$, and $50th$ quantiles, respectively. For other quantiles this effect is negative and 27,5% at the $90th$ quantile. This, negative relation stems from the fact that the occupations with the highest average wages has the lowest occupational mobility.

When we let $OccMobility$ to have different values, interpreting the results becomes difficult. In order to manage this problem, assume that $OccMobility$ is continuous but average $OccMobility$ in the population is only 5% (which is the highest occupational mobility level among ISCO08 2-Digit Codes' first three the major groups). Then, mobility effect at 20% point increase in $ReerMobility$ (which can be translated as a decrease in the value of TL) leads to an increase in wages by 27.8% in the $10th$ quantile.

We also estimate separately the effect on the female and male sub samples. DID and UQR results suggest that the effect of $ReerMobility$ is greater for the males in every model, which suggest that males have higher occupational mobility.

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