LEARNING BY EXPORTING AND HETEROGENEITY IN POST-ENTRY EFFECTS

by

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Abstract

We examine the relationship between export entry and productivity of Turkish manufacturing firms using a rich longitudinal micro dataset of Turkish manufacturing firms in the period between 2006 and 2015. To alleviate the selection bias problem, we employ propensity score reweighting and propensity score matching methods. Another goal of this study is to investigate whether some characteristics, namely firm age, import status, import intensity, export intensity and export destinations by income level, lead to heterogeneity in treatment effects. Our main findings can be listed as follows: i) Both self-selection and learning by exporting hypotheses are verified; ii) Increasing export intensity leads to additional productivity gains for export starters; iii) There is some evidence indicating that starter firms that export to both high income and low income destinations experience larger productivity gains; iv) No noteworthy evidence is found regarding impact of import status, import intensity and age on the treatment effect.

Keywords: Trade; Productivity; Self-selection; Learning by exporting; Post-entry effects

İHRACAT YAPARAK ÖĞRENME VE İHRACAT BAŞLANGICI SONRASI ETKİLERDE HETEROJENLİK

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Özet

Bu çalışmada 2006-2015 yıl aralığını içeren ve Türk imalat firmalarını barındıran zengin mikro panel veri tabanını kullanarak ihracata giriş ve Türk imalat firmalarının verimliliği arasındaki ilişkiyi inceliyoruz. Seçime bağlı yanlılık sorununu azaltmak için eğilim skorları yeniden ağırlıklandırma (propensity score reweighting) ve eğilim skorları eşleştirmesi (propensity score matching) methodlarını kullanıyoruz. Bu çalışmanın bir diğer amacı da firma yaşı, ithalat durumu, ithalat yoğunluğu, ihracat yoğunluğu ve gelir seviyesine göre ihracat istikameti gibi bazı firma özelliklerinin uygulamanın etkilerinde heterojenliğe sebep olup olmadığını araştırmaktır. Çalışmamızın ana sonuçları şöyle sıralanabilir: i) Hem kendi kendini seçme ve ihracat yaparak öğrenme hipotezleri doğrulanmıştır; ii) İhracat yoğunluğunda artış ihracata başlayan firmaların verimliliklerinde ilave artışa sebebiyet vermektedir.; iii) İhracata başlayan firmalardan hem düşük gelirli hem de yüksek gelirli ülkelere ihracat yapanların verimliliklerinin ihracata başlayan diğer firmalarınkine göre daha fazla arttığı görülmüştür; iv) İthalat durumu, ithalat yoğunluğu ve firma yaşının uygulamanın etkisi üzerinde herhangi bir etkisi olmadığı bulunmuştur.

Anahtar Kelimeler: Ticaret; Verimlilik; Kendi kendine seçilme; İhracat yaparak öğrenme; Başlangıç sonrası etkiler

To my wife

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1 INTRODUCTION

Exporting is often considered as an important way to boost economic growth by policymakers. In this paper by examining the linkage between exporting and firm productivity in Turkish context, we aim to provide further information on this subject to both policymakers and researchers. The relationship between exporting and firm productivity has been examined empirically in the economics literature.[1] Findings of previous empirical studies indicate that exporting firms exhibit higher productivity levels than non-exporting firms do. To explain this positive correlation between exporting and firm performance two mechanisms which are not mutually exclusive are considered in the literature. The first mechanism suggests that firms with higher initial productivity levels enter foreign markets. The intuition behind this hypothesis is that selling goods in a foreign market comes with additional costs to the firm. Transportation, distribution and marketing costs, costs to adjust products to foreign markets are some of the potential extra costs that a firm may need to bear when it enters a foreign market. Existence of such entry costs prevents less productive firms from entering foreign markets. The second mechanism suggests that after export entry, exporting firms experience additional productivity improvements. In the literature, the first mechanism is widely accepted. Firms that start exporting show higher productivity levels prior to export entry. However, for the second mechanism, which is called the ”learning by exporting” (LBE) hypothesis in the literature, there is no clear consensus. Clerides et al. (1998) for Colombia, Morocco and Mexico; Delgado et al. (2002) for Spain; Bernard and Jensen (2005) for US and Wagner (2007) for Germany provide evidence for self-selection but find no clear evidence of LBE.[2] On the other hand, there are also studies that verify LBE. De Loecker(2007) for Slovenia, Mallick and Yang (2013) for India, Girma et al. (2004) for UK and Maggioni (2012) and Cebeci (2014) for Turkey provide evidence for learning by exporting.

Some of the papers in the literature also draw attention to heterogeneous post-entry effects. De Loecker (2007) and Cebeci (2014) investigate how income level of export destination affects the productivity of an exporter firm. Maggioni (2012) also investigates whether export destination affects the firm level productivity. However, while De Loecker (2007) and Cebeci (2014) use income levels to categorize export destinations, Maggioni (2012) uses the technological gap between the domestic sector and the destination. Further, she explores the link between exporting and importing. She finds that compared to non-exporters import share of firms that start exporting increase after the export entry. In

[1] see Wagner (2007) and Wagner (2012)

[2] Results of Clerides et al. (1998) do not support the LBE hypothesis, except for Moroccan apparel and leather producers. Delgado et al. (2002) couldn't find statistically significant productivity growth difference between export starters and non-exporters after export entry. However, when the sample is restricted to younger firms, the LBE hypothesis is verified. Bernard and Jensen (2004) and Wagner (2007) report no evidence of LBE.

addition, her findings imply that firms that start export and import simultaneously experience extra productivity gains. On the other hand, exporters that start export and import in different years do not experience such extra gains. Additional gains might be a joint impact of exporting and importing on productivity or it can be direct impact of importing. Anderson and Lööf (2009), focus on the impact of export intensity on the learning effects of the exporters via using a panel data on Swedish manufacturing firms. Their results imply that the higher the intensity of exporting, the larger the learning by exporting outcomes. They define persistent exporters as firms that export throughout the whole period and temporary exporters as the firms that export occasionally. Given these definitions their findings suggest that LBE hypothesis works for small persistent firms. They also report that large firms should both export persistently and intensely to experience additional productivity benefits. Similarly, Girma et al. (2004) question whether growth rate of export intensity influences the productivity effect of exporting. Their findings suggest that a rise in export share results in additional productivity growth in the period after entry. Baldwin and Gu (2003) inquire whether age of a firm has an impact on post-entry productivity gains. Using Annual Surveys of Manufactures which covers whole manufacturing sector of Canada they show that young firms benefit from entry more than older firms in terms of labor productivity. In this paper, we also examine export intensity, import status, firm age, income level of export destinations which might lead heterogeneity in post entry effects.

Relation between exporting and productivity of Turkish manufacturing firms is studied by several authors.[3] To our knowledge, the earliest relevant work that uses Turkish data is by Yasar and Rejesus (2005). They use data on Turkish apparel, textile and motor vehicles and parts industries. Via using a combination of propensity score matching (PSM) and difference in differences (DID) methods they provide evidence on self selection into exporting and learning by exporting. Similarly, Aldan and Gunay (2008), Maggioni (2012) Dalgic et al.(2014) and Cebeci (2014) employ PSM and DID methods together to investigate the impact of exporting on productivity. Only Dalgic et al (2015) focus on self-selection. While Maggioni (2012), Cebeci (2014) Dalgic et al. (2014) and Dalgic et al. (2015) use Turkstat's Annual Industry and Service Statistics and Foreign Trade Statistics, Aldan and Gunay (2008) use a dataset which is provided by Central Bank of Turkey and which contains balance sheets and income statements of Turkish firms in the manufacturing sector. While Dalgic et al.(2014) and Dalgic et al. (2015) provide evidence only on learning by exporting and self-selection respectively, the rest of the papers provide evidence on both of the mechanisms.

With this study, we contribute to the literature by providing further evidence on the impact of exporting on productivity of manufacturing firms that operate in Turkey. As

[3]Yasar and Rejesus (2005), Aldan and Gunay (2008), Maggioni (2012), Cebeci (2014), Dalgic et al. (2014), Dalgic et al. (2015)

findings of Busso et al. (2009) indicate in terms of finite sample properties, propensity score reweighting performs better than propensity score matching methods. For that reason, in our analysis we use propensity score reweighting method in addition to propensity score matching. This is the first study that employs propensity score reweighting to investigate LBE hypothesis in Turkish context. Secondly, to our information, this paper is the first paper which uses the trade section of Annual Industry and Service Surveys, which has been made available only recently, rather than Foreign Trade Statistics. As it will be discussed in Section 2, trade information that is provided by Annual Industry and Service Statistics is more reliable than the trade information provided by Foreign Trade Statistics. For that reason, we hope that our findings are more informative than findings of previous studies. Thirdly, we control for several factors that are discussed in the literature regarding heterogeneity in post-entry effects and examine how they affect post entry effects in a single study.

The rest of the paper is organized in following way. In section 2, we explain the data and the variables we use. In section 3, we present the methods we employ to investigate the hypotheses. Section 4 presents the results. Finally, Section 5 concludes the paper.

2 DATA

In this paper, we use the Annual Industry and Service Statistics (AISS) which is compiled by Turkish Statistical Institute (Turkstat). The dataset is firm-level panel data and it contains all firms that operate in Turkey and have at least 20 employees. Firms with less than 20 employees are represented on a sampling basis.[4] In the data, sectoral information for each firm is specified in accordance with NACE Rev. 2 classification. This study focuses on the manufacturing sector in the period between 2006 and 2015. After a data cleaning procedure, we are left with 49,657 firms, for a total of 251,712 observations. For the analysis the following variables are used from the dataset: firm ID, import and export status, sector information (2-digit NACE Rev. 2), total investments, foreign ownership status, value added at factor cost, employment level, materials, inventories, sales, total wages, energy consumption and depreciation level.[5] Average wage and labor productivity is calculated by dividing total wages and value added at cost to employment level of the firm respectively. Lastly, capital is estimated by using depreciation, total investments, value added, materials and employment variables. For the estimation procedure see the Appendix. We also need firm age for the analysis and to have that information we make use of the Business Registry dataset which is also provided by Turkstat.

Some of the related previous works on Turkey[6] use Foreign Trade Statistics (FTS) of Turkstat to retrieve information on export status of firms. Rather than using the FTS, we obtain information on export status of the firm and total value of exported goods directly from Annual Industry and Service Statistics. There is a significant difference between those two dataset regarding how export information is gathered. In FTS, a firm which sends goods to customs is considered as an exporter, regardless of whether the firm in question is also the producer of these goods. However, a manufacturing firm which sends its goods to foreign countries via an intermediary firm is not considered as an exporter firm. On the other hand, in AISS provides information not only on firms that export directly, but also on firms that export via an intermediary firm; this allows us to consider the latter as exporters as well. Note that within AISS both exporter which exports indirectly and its intermediary firm is considered as exporter. Within manufacturing sector there cannot be firms whose main activity is trading and by focusing on only manufacturing firms we avoid from taking into account exporting firms which mainly sell products that they did not produce.

In order to observe difference between AISS and FTS, firstly we merge AISS with FTS by year and firm ID and keep matched firms and firms that are only observed in

[4]Firms with less than 20 employees are unlikely to be observed in consecutive years in the data. Since we require both control and treatment firms to be observed for at least 5 consecutive years, majority of the firms that we use in our analysis have more than 20 employees.

[5]All nominal values are deflated using 2 digit NACE Rev. 2 price indices that are provided by Turkstat.

[6]Maggioni (2012), Cebeci (2014), Dalgic et al. (2014) and Dalgic et al. (2015)

AISS. Afterwards, we investigate how many of the firms are regarded as exporters by each dataset. Further, using export values that are provided by each dataset, we compare total value of exports for each year. Figure 1 and Figure 2 illustrate the number of exporters and the total value of exports for each year, respectively. It is evident from figures that FTS provides information only about a subset of exporters. Since we aim to examine how export entry affects productivity of producers, we think that exporter information that is provided in AISS is more suitable. Using FTS to retrieve export information might lead one to disregard many manufacturing companies which export indirectly.

Figure 1: Total Number of Exporters in Manufacturing According to Datasets

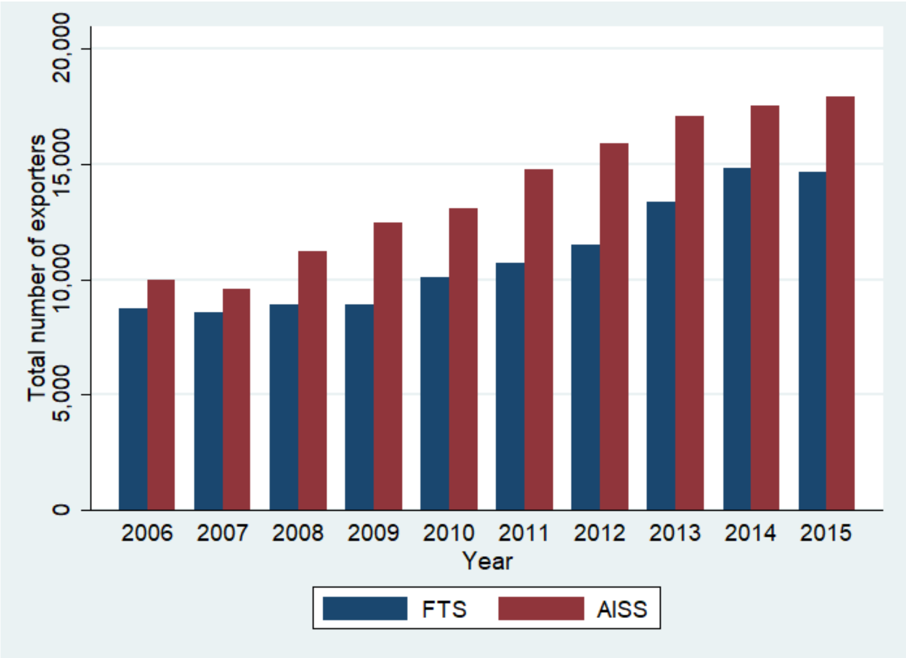
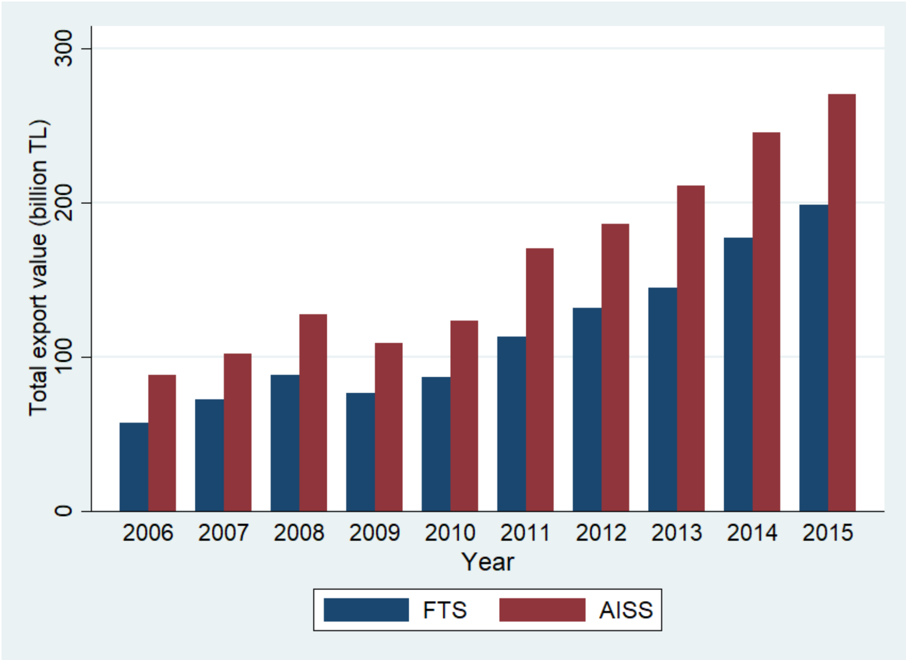


Figure 2: Total Value of Exports in Manufacturing According to Datasets



We aim to inquire whether treatment effect varies by export destination. Unfortunately, AISS does not provide information on export destination of exporters. For only this specific investigation of how treatment effect is influenced by export destinations, we make use of FTS. While doing so, we merge AISS and FTS datasets and use treatment and control firms that are observed within both of the datasets only. Note that FTS only contains information about direct exports. Hence, destination information we obtain from it might be deficient if a firm exports some destinations via an intermediary firm.

Table 1: Probit Regression Results

Outcome variable	LP	employee
Export start	.3485** (.0212)	.0009** (.0001)

**: Significant at 5% significance level.

3 METHODOLOGY

In this study, treatment is starting to export and we define a treated firm as a firm that exports at least for 3 consecutive years, starting with export entry year and that is not observed as an exporter prior to the export entry. We restrict the treatment sample to firms that are observed at least for 2 years before exporting starts. In the article, we will use treated firm, export starter and starter interchangeably. Control firms are defined as firms that never export and are observed for at least 5 consecutive years. Further, we use only the observations of these control firms where they are observed consecutively at least 5 years. Firms that do not belong to treatment or control groups are removed from the sample and we remain with 6276 firms for a total of 40,398 observations. We do all our analyses on this set of observations and from now on we will consider this set of observations as our sample. Here, it is important to note that in the relevant literature how (export) starter is defined varies. For example, in some of the papers in the literature starters are defined as firms that start exporting and are observed as exporter after initial export entry. In our study, we prefer to use a less stricter definition to have a larger set of treatment firms.

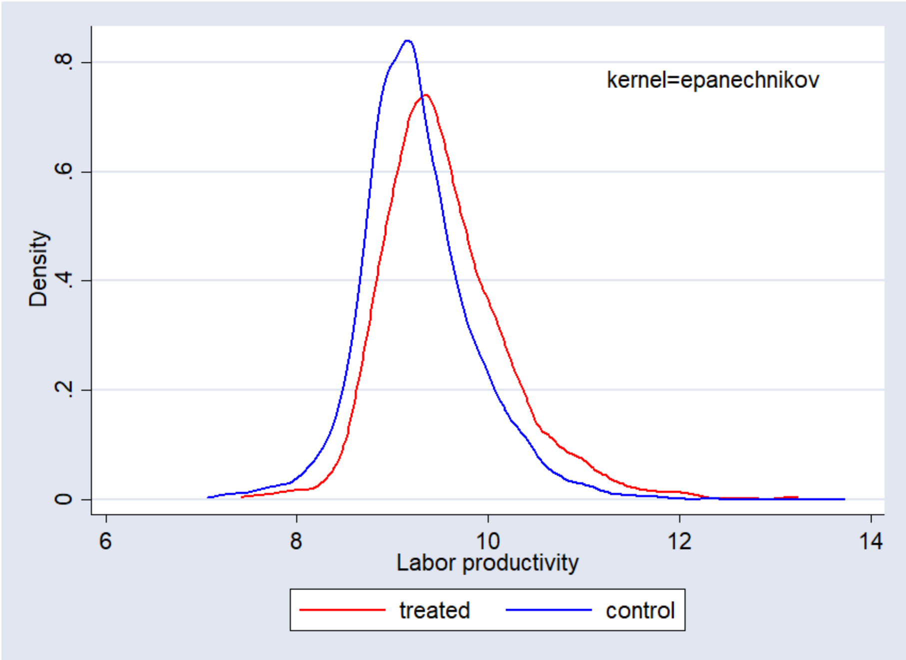
3.1 Self Selection

The main objective of this subsection is to investigate whether manufacturing firms are selected into treatment randomly. To examine selection into exporting, we first reduce the sample to pre-export entry year of treated firms and all observations of control firms. On this subsample, the following probit model is employed:

$$Pr(START_{i,t} = 1) = f(LP_{i,t-1}, Employment_{i,t-1}, Year_{i,t-1}) \tag{1}$$

where $START$, LP and $Employment$ indicate whether firm start exporting, firm's labor productivity in natural logarithm form and number of employees respectively. Results of probit regression is illustrated in Table 1.

Figure 3: Distribution of Pre-Entry Productivity for Treated and Control Firms



We also plot the distribution of pre-entry firm productivity to visualize selection pattern of firms. As illustrated in Figure 3 distribution of treatment firms lies to the right of distribution of control firms. The figure and results of the probit model indicate that selection into exporting is non-random and firms with higher productivity levels are more likely to start exporting.

3.2 Learning by Exporting

We aim to investigate average treatment effect on treated (ATT). Alternatively stated, we examine how treated firms' outcomes differ from their counterfactuals' on average. Estimation of treatment effect requires counterfactuals of firms, however it is impossible to observe a firm while exporting and while not exporting at the same time. To deal with this problem one might consider using non-exporters as counterfactuals of export starter firms. Nevertheless if there is a selection of firms into treatment then the results will be biased. As discussed in the previous section, firms are not selected into treatment randomly. To control for selection which we assume to be based on time-variant observable factors, we employ two different propensity score methods: propensity score matching (PSM) and propensity score re-weighting methods. We use propensity score reweighting in order to get our main results in the estimation of the treatment effects. Additionally, we use PSM which is the more commonly used one and show that our main results are consistent with the results of PSM.

3.2.1 Propensity Score Reweighting

As our main method we employ propensity score reweighting which performs better than propensity score matching in terms of finite sample properties. As the first step of this method, for each firm we estimate the probability of being treated (propensity score of firm) using relevant, observable firms characteristics (covariates) that are assumed to influence both the probability of being treated and outcome simultaneously. In this study, the covariates are determined as wage per employee, capital per employee, import intensity, employment and labor productivity.[7] Import intensity is defined as the share of total imports in sales of the firm. Given the covariates, we define a logit model that is used to estimate the probability of starting export. We also include year dummies to the model to control for year fixed effects. The model is presented below:

$$\begin{aligned} Pr(START_{i,t}=1) = f(&LP_{i,t-1}, Wage_{i,t-1}, Employment_{i,t-1}, Capital_{i,t-1}, \\ &Impint_{i,t-1}, Year_{i,t-1}) \end{aligned} \tag{2}$$

where LP, $Wage$, $Employment$, $Capital$ and $Impint$ indicate labor productivity, wage per employee, number of employees, capital per employee and import intensity respectively. We estimate the logit model on all control observations and pre-entry observation of treatment firms.[8]

After propensity scores are estimated, they are used to weight treatment and control observations. More specifically, the weights are used in the weighted regression. In ATT estimation each treatment observation receives a weight of 1 and each control observation receives a weight of p^*/(1-p^*) where p^* indicates the propensity score assigned to an observation. Following Guadalupe et al (2012) and Stiebale and Vencappa (2016) we sum the weights of control firms. In that way, we assign a single weight for each control and treatment firm.[9] T-tests and other statistical tests of hypothesis are affected by sample size and hence they might be misleading as measures of balance. For that reason, after the weights are determined, we prefer to use standardized percentage bias, which is not affected by sample size, to evaluate balance of covariates (Austin 2009).

Later, including firm fixed effects we run a weighted regression on control and treatment firms. To estimate ATT, the following regression model is employed:

$$Y_{i,t} = \alpha + \beta_1 P_i^1 + \beta_2 P_i^2 + \beta_3 P_i^3 + \beta_4 P_i^4 + \mu d_t + f_i + \epsilon_{i,t} \tag{3}$$

where d_t and f_i indicate year dummies and firm fixed effects, respectively. Here the dependent variable $Y_{i,t}$ is labor productivity or labor productivity growth. We are partic-

[7] Except for import intensity, the covariates are in natural logarithmic form.

[8] The results of logit regression shows that all the covariates are significant. For the sake of brevity relevant results are not presented but they are available upon request.

[9] To prevent extreme weights, weights that exceed that of the 99 percentile are assigned to the weight of the 99 percentile.

ularly interested in the impact of export entry on the outcome variable within the first 3 years, for that reason we include dummy variables P^1, P^2, P^3. $P^1 = 1$ if observation represents entry year of a treatment firm else, $P^1 = 0$. Similarly, $P^2 = 1(P^3 = 1)$ if the observation represents the treatment firm's second(third) year of entry. Otherwise, $P^2 = 0(P^3 = 0)$. Also, we add P_i^4 to the model in order to check how productivity differs from control firms on average after the third year of the entry.[10] P_i^4 takes 1 if the observation represents the treatment firm's any year after the third year of the entry.

3.2.2 Propensity Score Matching

The PSM algorithm matches treatment firms with control firms that have similar relevant pre-treatment characteristics and use those control firms to approximate counterfactuals of treated firms. First, we employ the same propensity score estimation method as in the previous subsection on all control observations and pre-entry observation of treatment observation of treatment firms. After estimating the propensity score, nearest neighbor matching with replacement is performed.[11] To avoid the potential risk of comparing firm observations under significantly distinct macroeconomic conditions, we restrict matched pairs to come from the same year. In order to assess the quality of matching we check standardized percentage bias of covariates after the matching. By performing 1-1 matching, we mitigate selection bias on observables. However, potential evaluation bias can be reduced further by removing the effects of unobservable time invariant differences between treatment and control firms (Blundell and Costa Dias, 2000). Therefore, we run a regression on the matched firm sample, with firm fixed effects and year effects. Since we perform 1-1 matching with replacement, control firms within matched sample are weighted according to number of times they are used as counterfactual. The regression model has the following form:

$$Y_{i,t} = \alpha + \beta_1 P_i^1 + \beta_2 P_i^2 + \beta_3 P_i^3 + \beta_4 P_i^4 + \mu d_t + f_i + \epsilon_{i,t} \tag{4}$$

where μd_t and f_i indicate year dummies and firm fixed effects respectively. In this regression model, as outcome variable we use both labor productivity and labor productivity growth. Again, P^1, P^2, P^3 and P_i^4 indicate first year of entry, second year of entry and third year of entry and years after third year of entry for treatment firms respectively.

3.2.3 Extensions: Heterogeneity in Post Entry Effects

As stated in the literature, impact of exporting on the productivity of firms may vary by some firm characteristics such as firm age, import status and intensity, export intensity and income level of export destination. Baldwin and Gu (2003) state that young firms have

[10] It is important to note that not all export starters keep exporting after the third year.
[11] We use only observations within the common support.

less time to establish information networks which enable the firms to obtain knowledge on technologies that might boost the productivity of the firms. Also, often younger firms have access to fewer technologies (Baldwin and Diverty 1995). For those reasons, young firms might learn more during exporting as Baldwin and Gu (2003) suggest.

Via importing, firms can access high quality intermediate inputs to produce more sophisticated final goods (Bas and Strauss-Kahn (2015); Fan et al. (2015)). Further, importing intermediate inputs can help firms to increase product variety (Goldberg et al., 2010). Results of Feng et al.(2016) suggest that importing intermediate goods can increase the export value of exporting firms and help firms to export to high income destinations more intensely. In these ways, importing may indirectly lead exporters to gain more from export activities in terms of the productivity.[12] Findings of Maggioni (2012) indicates that exporting might increase import share of the export starters. Further, she shows that firms which start exporting and importing simultaneously experience higher productivity gains than firms that start exporting only. The reason of higher gains is not identified in the paper but it might be a joint effect of exporting and importing or a direct effect of importing. To estimate independent impact of export entry on productivity and potential joint impact of export entry and importing, import status/intensity should be controlled.

Destination of exports might affect magnitude of productivity gains. While exporting to developed, high income countries exporters might acquire advanced technologies and more knowledge. Also, exporters may have more incentive to be innovative if competition is higher in foreign markets. For those reasons, it is expected that treatment effects are larger for starters that export to high income regions. In the literature there are papers providing evidence on heterogeneity in post entry effects with respect to export destinations. De Loecker (2007) finds that starter firms that export only to high income destinations experience higher productivity gains than starters that export only to low income destinations. Cebeci (2014) shows that while starters that export to high income destinations experience productivity gains, there are no significant productivity gains for starters that export to low income destinations.

Another factor that may affect magnitude of learning effects is export intensity. How much a firm learn from exporting might be related with how intensely firm exports. Findings of Girma et al. (2004) and Anderson and Lööf (2009) supports that increasing export intensity influences productivity positively.

Previous findings in the literature and arguments presented above motivate us to examine how post-entry effects change according to these firm characteristics. For this investigation we prefer to use propensity score reweighting. Instead of inquiring heterogeneous post-entry effects for the first 3 years of entry separately, we focus on their average. For

[12] Importing may also directly lead productivity gains and export entry. By using import intensity as a covariate in the propensity score estimation we take these into account and make sure that post entry effects are not driven directly by importing but exporting.

that reason, treatment firms' 4th year of entry and years following it are removed from the sample. To examine how import status, import intensity and firm age influence the impact of export entry on productivity, the following model is used:[13]

$$Y_{i,t} = \alpha + \beta_1 treatment_i + \beta_2 X_{i,t} + \beta_3 treatment_i * X_{i,t} + \mu d_t + f_i + \epsilon_{i,t} \tag{5}$$

where d_t, f_i indicate year dummies, time invariant firm characteristics respectively and $X_{i,t}$ indicates import status or import intensity or firm age. In the model above, $treatment_i = 1$ if firm i is exporting and $treatment = 0$ if firm i is not exporting. Since we reduced sample to treatment firms and control firms, all exporting firms are treatment firms. Outcome variables are labor productivity and labor productivity growth. In this model, the coefficient of the interaction term indicates how treatment effect varies with the control variable.

Export intensity and export destination are characteristics that are defined for exporting firms and when previous model is used to investigate how these characteristics affect impact of treatment collinearity problem occurs. To examine how export intensity[14] and export destination impact the effect of export entry on productivity, we run the following regression model:

$$Y_{i,t} = \alpha + \beta \chi_{i,t} + \mu d_t + f_i + \epsilon_{i,t} \tag{6}$$

where $\chi_{i,t}$, d_t, f_i indicates export variables, year dummies and time invariant firm characteristics respectively. Export variables are export intensity and categorical export destination variable. Again, outcome variables are labor productivity and labor productivity growth. Export intensity is a continuous variable and control firms' export intensity is 0. Using World Bank's 2010 gross national income classification for countries, we define two categorical destination variables by income level.[15] World Bank groups countries as low, lower middle, upper middle and high income. Turkey is regarded within the upper middle income group. We simplify this classification and define countries that are in the same or lower income group with Turkey as low income countries and define the rest of the countries as high income. The first destination variable separates observations into three groups: observations where firms export to at least one high income destination, ob-

[13]Note that Maggioni (2012) examines how productivity gains of starters that start importing and exporting simultaneously and starters that start exporting only differ. We do not ask the same question with her. Instead, we question whether import status and import intensity have an influence on the magnitude of treatment effects.

[14]Similar to import intensity, export intensity is defined as ratio of exports to total sales.

[15]Some of the export destinations do not appear in the World Bank's classification(e.g.,. Cook Islands, Falkland Islands). If such destinations are in free association with another country or they are territory of another country then it is assumed that their income level is the same with the country they are associated with. Otherwise, destinations are defined within the low income group.

servations where firms export only to low income destinations and control observations. The second destination variable separates observations into four groups: observations where firms export only high income destinations, observations where firms export only low income destinations, observations where firms export to both type of destinations and control observations.

Although the Annual Industry and Service Statistics (AISS) provides more accurate information regarding export status and total export value than the Foreign Trade Statistics (FTS), AISS does not contain information about export destination countries. For that reason, we use the FTS to find export destinations of treatment firms. When we merge the two datasets, we obtain export destination information for only a subgroup of our treatment firms[16] and we employ weighted regression analysis on control firms and this subgroup of treatment observations.

[16]That is because of the fact that in FTS only direct exporters are regarded as exporter.

4 RESULTS

In this section we present our main findings. As is expressed in the beginning of the previous section, the analyses are performed on the sample of observations of treatment and control firms. This sample consists of observations of non-exporter firms where they are observed consecutively at least five years and observations of export entrants where they are observed at least two consecutive years prior to entry and export at least three consecutive years starting with the entry year.

Table 2: Absolute Standardized Percentage Bias

Method	Wage per employee	Capital per employee	Employment	Labor productivity	Import intensity
Propensity Score Matching	12.494	6.411	15.408	3.860	14.821
Propensity Score Reweighting	12.535	10.382	5.872	2.271	5.460

Both after 1-1 propensity score matching with replacement and propensity score reweighting, we check standardized percentage bias of covariates as a measure of balance. If absolute standardized percentage bias of a covariate exceeds an upper limit then it is concluded that balance is not satisfied for that specific covariate. However, in the literature there is no consensus on what upper limit should be. Rosenbaum and Rubin (1985) suggest that a value more than 20 percent is too large to conclude that covariate is balanced. In this paper, we use 20 percent as upper limit of the measure. Table 2 illustrates absolute standardized percentage bias of covariates for both matching and reweighting. Clearly, balance is satisfied in each propensity score method.

Table 3: ATT Effects: Propensity Score Reweighting Estimates

Outcome variable	1st year (entry year)	2nd year	3rd year	Years after 3rd year of entry
LP	0.063** (0.014)	0.084** (0.016)	0.095** (0.017)	0.142** (0.021)
LP growth	0.042** (0.020)	0.010 (0.017)	0.004 (0.017)	0.019 (0.016)

,*: Significant at 5% significance level.
When outcome variable is LP number of observations and number of firms are 38907 and 6276, respectively. When outcome variable is LP growth number of observations and number of firms are 38840 and 6276, respectively.

Main results with respect to LBE are presented in Tables 3 and 4. In Table 3, results of propensity score reweighting are provided. As shown in Table 3, the impact of export entry on productivity during the entry year and following years is positive and significant.[17] This means compared to control firms, treatment firms experience productivity gains when they start exporting. It is also found that impact of export entry has positive and significant effect on the productivity growth for the entry year. This finding implies that in the year of entry starters move to a higher productivity growth path with respect to their previous growth paths and stay in this new path in the following years of entry. Note that the estimated coefficients in the regression where the outcome variable is LP increase over time and this also signals an increase in annual productivity gains. Considering increasing coefficients and significant impact of export entry on the productivity growth we expect that annual productivity gains of export starters rise over time. In order to verify this, we check whether these coefficients of export years vary significantly using one-tailed and two tailed tests. We fail to reject the null hypothesis that coefficient of the first year and the second year are equal. Similarly, we fail to reject the null hypothesis that coefficient of the second year and the third year are equal. However, the null hypotheses that coefficient of the first year and the third year are equal and coefficient of the third year and coefficient for years after 3rd year of entry are equal, are rejected. Further, using one-tailed tests we find that coefficient of third year is significantly larger than the coefficient of first year and coefficient for years after 3rd year of entry is significantly larger than the coefficient of the third year.[18] Results of hypothesis tests support that productivity gains of the export starters increase over time.

Results of propensity score matching are presented in Table 4. Overall, results of the matching method are consistent with the results of the propensity score reweighting. As Table 4 illustrates, when outcome variable is labor productivity, coefficients are positive and impact of treatment on the productivity is significant. It is also found that impact of export entry has significant effect on the productivity growth for the entry year. This finding is supported by the fact that coefficients in the regression where the outcome variable is LP increase over time. Here, we also use one-tailed an two-tailed tests to examine whether coefficients in the regression where the outcome variable is LP differ from each other significantly. Results of the tests indicates that the coefficient of the second year is significantly larger than the coefficient of the first year. Also, it is found that coefficient of the fourth year is significantly larger than the coefficient of the third year. However, we failed to reject the null hypothesis that coefficient of second and third

[17] Note that our starter definition requires export entrants to export for at least 3 consecutive years, therefore some of the starters in our sample may stop exporting at any point after 3 years of exporting. This means that coefficient for years after 3rd year of entry might be even larger if starters were consisting of firms that keep exporting after 3rd year of entry.

[18] For the sake of brevity results of hypothesis tests are not illustrated. However, they are available upon request.

year of entry are equal. With both methods we find that export entry leads to higher productivity gains and exporters move to higher productivity path in the first year of the entry and their productivity gains increase over time.

Table 4: ATT Effects: PSM-Fixed Effect Model Estimates

Outcome variable	1st year (entry year)	2nd year	3rd year	Years after 3rd year of entry
LP	0.066** (0.023)	0.100** (0.027)	0.116** (0.030)	0.168** (0.041)
LP growth	0.047*** (0.027)	0.021 (0.023)	0.012 (0.025)	0.027 (0.028)

,*: Significant at 5%, 10% significance level respectively.
When outcome variable is LP number of observations and number of firms are 17481 and 1451, respectively. When outcome variable is LP growth number of observations and number of firms are 17414 and 1451, respectively.

In this study, using propensity score reweighting we also investigate how firm age, import status, import and export intensity and export destination influence the treatment effect. Table 5 presents results of regression model (5) and Table 6 presents results of regression model (6). As illustrated in Table 5, when the outcome variable is labor productivity coefficient of interaction between age and treatment has a negative value. However, interaction is insignificant. Age has no independent influence on productivity either. When the outcome variable is the productivity growth, the coefficient of the interaction of treatment and age is insignificant but age has a significant independent effect on the productivity growth.Further, Table 5 presents results regarding importing. Neither import status nor import intensity have a significant impact on the scope of treatment effects. In contrast to our expectations importing does not influence learning effects. Also, both import status and import intensity have no significant independent effect on the outcome variables. Another important point is that when age and import status/intensity are controlled separately, impact of treatment on productivity is found to be positive and significant.

Table 5: Impact of age, import status and import intensity on treatment effect

	Independent Variables	Outcome Variable: LP	Outcome Variable: LP Growth
Regression 1	Treatment dummy	0.108** (0.026)	-0.005 (0.029)
	Age	-0.002 (0.022)	0.006** (0.002)
	Interaction	-0.002 (0.001)	0.002 (0.002)
Regression 2	Treatment dummy	0.074** (0.014)	0.015 (0.016)
	Import Status	0.012 (0.017)	-0.014 (0.019)
	Interaction	0.019 (0.023)	0.025 (0.029)
Regression 3	Treatment dummy	0.067** (0.013)	0.017 (0.014)
	Import Intensity	0.010 (0.041)	-0.015 (0.046)
	Interaction	0.004 (0.077)	-0.036 (0.088)

**: Significant at 5% significance level.
In the regressions 6276 firms are used. For outcome variables LP and LP growth number of observations are 36533 and 36497, respectively. As the outcome variable is different for the regressions, number of observations differ dependently.

Finally, Table 6 provides information regarding whether treatment effect varies according to export intensity and export destination. We run regression for model (6) on the sample and coefficients of export intensity and export destination imply how treatment effect on the productivity vary with respect to them. As it is indicated in Table 6, export intensity has a significant positive impact on labor productivity. Hence, it is concluded that as export intensity increases impact of treatment on the productivity rises. Further, export intensity has a significant influence on productivity growth. Results of regression 2 and 3 in Table 6 imply that for starters exporting to any destination affects productivity significantly. After regression 2 we test whether coefficient of exporting to only low income destination and coefficient of exporting to at least 1 high income destination differ significantly. We failed to reject the null hypothesis that coefficients are equal. We also test whether destination variables have significantly different coefficients after regression 3. We failed to reject the null hypothesis that exporting only to high income and only to low income have same coefficients. Similarly, we failed to reject the hypothesis that exporting only to low income destinations and to both destination types have same coefficients. However, it is found that at a 10% level of significance the coefficient of exporting to both destination types have significantly larger than the coefficient of exporting only to high income destinations. Further it is found that, while exporting to only one type of destinations have no significant effect on productivity growth exporting to both destination types have significant positive impact on the productivity growth. Overall, there is some evidence which supports that exporting both type of destinations provide additional gains for export starters.

Table 6: Impact of export intensity and export destinations on treatment effect

	Independent Variables	Outcome Variable: LP	Outcome Variable: LP Growth
Regression 1	Export intensity	0.119** (0.028)	0.048*** (0.029)
Regression 2	Only low income	0.076** (0.018)	-0.001 (0.021)
	High income	0.075** (0.015)	0.028 (0.016)
Regression 3	Only low income	0.077** (0.018)	-0.0008 (0.021)
	Both	0.092** (0.018)	0.049** (0.021)
	Only high income	0.050** (0.019)	-0.002 (0.021)

,*: Significant at 5%, 10% significance level, respectively.
In the regressions 6276 firms are used. When the independent variable is export intensity, for outcome variables LP and LP growth number of observations are 36533 and 36497, respectively. When the independent variable is export destination, for outcome variables LP and LP growth number of observations are 36031 and 35995, respectively. Note that number of destinations are smaller when independent variable is export destination. To obtain information about export destinations we use FTS and since FTS provide information for a subset of exporters we lose some of the observations.

5 CONCLUSION

In this study, using a rich panel data of Turkish manufacturing firms we investigate the relation between export entry and firm productivity. For this investigation, we employ two distinct propensity score methods. Moreover, we examine several firm characteristics that might have an impact on the magnitude of the learning effects of exporting.

We find that more productive firms begin to export, and treatment firms experience productivity gains comparing to the control firms. In other words, we verify both self-selection and learning by exporting hypotheses. Among the firm characteristics we examine, only export intensity has a significant impact on the magnitude of the treatment effects. Similar to the findings of Girma et al. (2004) and Anderson and Lööf (2009), our findings suggest that as export intensity increases productivity gains rise as well. We also find some evidence regarding the influence of income level of export destination on the treatment effect. Our results imply that the firms that choose to export to both high income and low income destinations experience higher productivity gains than firms that export only low income or only high income destinations. It could be the case that treatment firms that export both type of destinations on average export larger number of countries than other starters that export only one type of destination. We also find that productivity gains from exporting only to low income does not differ significantly from exporting only to high income destinations. Certainly, our findings about export destinations are not in the same direction with the findings of De Loecker (2007) and Cebeci (2014). De Loecker (2007) finds the starters experience productivity gains and entrants that export only to high income destinations benefit more than entrants that export only to low income destinations in terms of productivity. Cebeci (2014) finds productivity gains for only the starters that export to high income destinations. The difference between findings might be due to several reasons. Firstly, while our productivity measure is labor productivity, theirs is total factor productivity.Further, De Loecker (2007) and Cebeci (2014) use a subsample of treatment firms that do not change their export destination by income level for the years they are observed to examine how destinations influence the treatment. However, we allow treatment firms to change their export destination by income from year to year and we use all the treatment firms in our analysis. Therefore, our results provide more detailed information regarding how treatment effect varies with respect to each destination type (low income, high income and both). Also, while De Loecker (2007) and Cebeci (2014) use propensity score matching, we use propensity score reweighting to examine heterogeneity in post-entry effects with respect to export destinations. Unlike findings of Baldwin and Gu (2003), our findings suggest that age has no significant impact on the magnitude of the treatment effect on the productivity. We also find that treatment effects do not vary with import status and import intensity. Moreover, the results suggest that importing has no significant impact on the productivity and productivity growth.

In this study, we define export entrants as firms which start export and export at least 3 consecutive years. However, not all export entrants export at least 3 consecutive years. There are also export entrants that exit from foreign markets before completing 3 consecutive years of export experience. Moreover, some firms export irregularly. In this study such entrants are ignored, and we only provide evidence regarding the starters that export at least 3 consecutive years.

It might be the case that, importing does not influence post entry effects immediately. Instead, it could take some time for importing to influence the magnitude of the treatment effect. Here, we examine whether importing has an immediate influence on post entry effects and fail to provide any evidence for it.

It is also important to note that, we do not examine how learning effects vary with imported capital and intermediate goods. Instead, we examine how total imports influence the magnitude for the learning effects due to limitations of the data set. However, type of imported products may have an influence on the magnitude of learning effects from exporting. Especially, imported capital and intermediate goods may help firms to upgrade their products or increase their product variety. In that way those import goods may encourage exporters to export intensely, enter new foreign markets and consequently learn more from exporting. If data is available, future studies may examine heterogeneity in LBE effects with respect to type of import goods in a detailed manner.

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7 APPENDIX: CAPITAL STOCK ESTIMATION

To estimate capital stock, we use perpetual investment method. This method requires investments, depreciation levels and initial capital stock for each firm. However, for some firms, depreciation level is missing in some years that they are observed. After all nominal values are deflated using 2-digit NACE Rev. 2 price indices, the regression model below is used to estimate missing depreciation levels:

$$Depr_{i,t} = \alpha + \beta_1 VA_{i,t} + \beta_2 Emp_{i,t} + \beta_3 Mat_{i,t} + \mu Year + \rho NaceRev2_i + \epsilon_{i,t} \quad (7)$$

where $Depr$, VA, Emp and Mat indicate depreciation level, value added, employment and material respectively. All of them are measured in logarithm. $Year$ and NaceRev2 indicate year dummies and 2-digit NaceRev2 sector dummies respectively.

Besides the depreciation levels, to use perpetual investment method we need to estimate initial capital level for firms. We estimate initial capital stock as ten times of initial depreciation. Finally, via using the equation below we estimate capital stock for firms:

$$Capital_t = Capital_{t-1} - Depr_{t-1} + TotInv_{t-1} \quad (8)$$

where Capital, Depr and TotInv indicate capital stock, depreciation and investment respectively.