ECONOMIC CONCENTRATION, LABOR MISALLOCATION AND EXCHANGE RATE SHOCKS

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ECONOMIC CONCENTRATION, LABOR MISALLOCATION AND EXCHANGE RATE SHOCKS

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DECLARATION OF ORIGINALITY

I, Nihan Nur Akhan, certify that:

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ABSTRACT

Economic Concentration, Labor Misallocation

and Exchange Rate Shocks

In this paper, I empirically investigate the effect of economic agglomeration on resource misallocation. Using data on the universe of manufacturing firms in Turkey between 2005 and 2015 and firm specific exchange rates as exogenous supply/demand shifters, I show that (i) industry level allocative efficiency is higher in agglomerated areas, (ii) firm-level distortions are lower in denser areas, (iii) thick labor markets mitigate the response of firm-level distortions to short-run fluctuations.

ÖZET

Ekonomik Yoğunlaşma, İşgücü Dağılımı ve Döviz Kuru Şokları

Bu analizde ekonomik aglomerasyonun kaynak dağılımı üzerinde olan etkisini ampirik olarak araştırdım. 2005-2015 yılları arasında, Türkiye'deki imalat firmalarını ve firma spesifik döviz kuru şoklarını arz/talep değiştiricisi olarak kullandım. Sonuçlarım, (i) ekonomik yığılmanın olduğu bölgelerde endüstri-seviyesindeki kaynak dağılımı etkinliğinin daha yüksek olduğunu, (ii) firma-seviyesindeki çarpıklıkların yoğun bölgelerde daha az olduğunu (iii) yoğun işgücü piyasalarının firma seviyesindeki çarpıklıkların kısa vadeli şoklara olan tepkisini azalttığını gösteriyor.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF APPENDIX TABLES

CHAPTER 1

INTRODUCTION

Resource misallocation, especially in developing countries, may substantially decrease the possible gains of trade liberalization, policy reforms and technological progress.[1] In general setup, when there is no variation in distortions, productivity should be equalized across all firms in the same sector so that each firm can optimally allocate resources according to their productivity level. However, due to labor and capital frictions the resources cannot freely move across firms even within same industry. In their pioneering paper, Hsieh and Klenow (2009) show that there can be substantial gains when market distortions are eliminated.

Potential sources of misallocation can mainly be classified into three categories. First, the tax and regulations can distort the firm's optimal decisions since different firm characteristics would lead to disparate outcomes. Second, discretionary provisions can be a potential source of misallocation if the government or other institutions like banks favour or punish specific firms. Lastly, market imperfections may result in misallocation[2]. It is also worth to note that misallocation is more evident and offers higher allocative efficient outcomes across developing countries.[3] Among developing countries, Turkey attracts a particular attention since the beginning of the 2000s due to the fact that it has experienced a high growth rate and a considerable level of resource inefficiency in manufacturing sectors at the same time.[4]

[1] See Hsieh and Klenow (2009); Restuccia and Rogerson (2008); Khandelwal et al. (2013)

[2] See Restuccia & Rogerson (2017) for more detail.

[3] See Bento and Restuccia (2017); Hsieh and Klenow (2009); Nguyen et al. (2016); Restuccia and Rogerson (2008); and Ryzhenkov (2016).

[4] See Nguyen et al. (2016).

In the last decade, literature examining misallocation connected this notion with financial frictions, trade or tax and regulations. However, the number of research examining the relationship between misallocation and agglomeration economies remained limited. In this paper, I empirically investigate the role of economic agglomeration on resource misallocation. In doing so, I distinguish between the long-run differences in the level of allocative efficiency and short-run fluctuations. Throughout the analysis, I mainly utilize Annual Industry and Service Statistics which is a confidential dataset for the years between 2005 and 2015 provided by by the Turkish Statistical Institute (TURKSTAT).

Firstly, in line with the literature that supports higher productivity premium in denser areas, I observe that productivity is right shifted in agglomerated areas. Then I check whether this premium has any implication on labor misallocation at the industry level. Secondly, in order to highlight the link between density of an area and firm-level distortions, I investigate the relationship between firm-level distortions and agglomeration economies. Lastly, I repeat this analysis with firm specific exchange rates that I constructed from Annual Trade Statistics dataset to examine the mediating role of labor market thickness on firm's responses.

In the estimation part, I tested these ideas with the Turkish manufacturing firms using Ordinary Least Square (OLS) Method. Treating Olley and Pakes (OP) covariance term between productivity and size as a dependent variable, I examine the relationship between industry level allocative efficiency and economic concentration. Moreover, I evaluate the statistical significance of the effects of the agglomeration economies on firm specific distortions using the gap between the marginal product and the marginal cost of labor as a proxy. Finally, I empirically propose that labor

market thickness in an area leads firms not only to have relatively less distortions on average but also to show smaller reactions to the short term exogenous shocks.

The rest of the paper is organized as follows: Chapter 2 summarizes the previous literature. Chapter 3 describes the data and provides a detailed description of construction of variables. Chapter 4 explains the methodology. Chapter 5 presents the results of the estimation analyses and finally, Chapter 6 concludes.

CHAPTER 2

LITERATURE REVIEW

This research broadly relates to the three main strands of the literature. The first strand is related to misallocation which is an expanding area in the literature. The second strand mainly relies on agglomeration economies. Finally, the third strand investigates the well-analysed subject, which is the link between exchange rates and employment.

Using the heterogeneous firm models like Melitz (2003) many research showed that distortions can have a substantial impact on resource allocation and offer a new explanation for the productivity differences across countries Indeed, Jones (2015) states that high level of distortions in poor countries and TFP differences are hypothetically related in misallocation literature by highlighting the importance of this area. In particular, developing countries experience a greater level of misallocation than developed countries due to the high level of potential distortions. Initiative paper of this literature, Hsieh and Klenow (2009) examined that the how distortions can lead aggregate TFP losses and show that efficiency gains from eliminating these distortions can be substantial. They found that in case of allocative improvement, resource allocation can increase TFP levels in China and India by 86.6%-115.1% and 100.4%-127.5% respectively. After this seminal paper, many papers combined misallocation with different strands of literature and offered significant results.[5]. In particular, Oberfield (2013) and Asker et al. (2014) focused on short-run adjustment process on measured allocative efficiency. Oberfield

[5]See Bartelsman et al. (2013), Restuccia and Rogerson (2008) Bento and Restuccia (2014) for dynamic dispersion, Midrigan and Xu (2014), Dias et al. (2016) and Gopinath et al. (2017) for the relationship between financial frictions and misallocation, Epifani and Gancia (2011), Berthou et al. (2017) for misallocation and trade.

(2013) related business cycle fluctuations with misallocation and suggested that misallocation between-industry caused by slow readjustment of capital and labor during the crisis of the early 1980s in Chile. While Asker et al. (2014) showed that a firm specific productivity shock with capital adjustment costs can explain both the dispersion and the volatility of marginal revenue product of capital across industries and countries as well as within countries.

From a regional perspective, Hsieh and Moretti (2017) calculated the total cost of labor misallocation by using constraints to new housing supply especially in New York and San Francisco Bay. Their results maintain that these restrictions reduce US growth rate by more than 50% for the 1964-2009 period. Furthermore, Fontagne and Santoni (2018) observed high level of allocative efficiency in agglomerated areas due to better matching between firms and workers.

Related to agglomeration economies, Behrens et al. (2014) stated that per capita production is higher in the larger cities. In their research, they explain these productivity differences with sorting, selection channels, and agglomeration economies. In addition, Baldwin and Okubo (2005) suggested that sorting and selection effects can have different implications for high and low productive firms. Rather than sorting or selection effect, Combes et al. (2012) associated the productivity differences mainly to agglomeration economies, which offers thick labor markets, higher level of infrastructure, service opportunities, public goods and technology spillovers. From the policy perspective, Okubo (2012) maintained that a subsidies correlated to the firm level profits can increase the average productivity in that region.

The last strand of literature related to my analysis is the well-analyzed subject between employment and exchange rate shocks. So far, many studies have examined the effect of exchange rate shocks to employment both at the industry-country, and firm levels such as Goldberg and Tracy (2000), Klein et al. (2003) or Ekholm et al (2012). In summary, at the firm level, responses are shaped throughout three channels, namely import cost, export price, and import competition channel. Indeed, Dai and Xu (2018) expanded Amiti et al. (2014) model and contribute to this literature by introducing the effect of firm specific exchange rates.

Combining these three different strands of literature, this research aims to answer the following questions: (i) How the economic concentration level affect both industry level allocative efficiency and firm level distortions? (ii) How does economic concentration mediate the firms' reactions of exchange rate shocks? Thus, this research contributes to the literature in two ways. Firstly, it relates employment concentration level to the misallocation at the industry level and presents a long-run result by carrying the advantage of using manufacturing firms dataset of a developing country, Turkey. Secondly, it presents the mediating role of labor market thickness on firm's short run adjustment decisions by investigating the effect of agglomeration economies and exchange rate shocks on firm level distortions.

CHAPTER 3

DATA AND DESCRIPTIVE STATISTICS

3.1 Data

For this research, I use Annual Industry and Service Statistics dataset provided by TURKSTAT on a representative sample of Turkish firms for the 2003-2015 period. Each year Annual Industry and Service Statistics dataset cover two different datasets. The main survey includes overall measures of the firms aggregated to the center along with the main industry code and the other provides plant level information on firms in the main survey. The main survey dataset contains information on firm's profile including employment, turnover, value added, industry codes according to Nomenclature of Economic Activities classification (NACE Revision). It also provides a detailed information on wage bills, location of the enterprises at the NUTS3K level. [6] But the dataset does not provide any information on asset level of the firms. However, plant level dataset variables are limited when compared to main survey dataset.[7] Therefore, throughout the analysis, I utilize both main and plant level datasets. Turkey is separated into 26 different NUTS2K level in both datasets. And the survey is designed to be representative at the 2 digit industry classification code and 26 NUTS2K regions.[8]

The survey started in 2003, but in order to increase data quality, the time period for this analysis is chosen as 2005-2015. Almost from 100,000 to 180,000 number of different firms were surveyed each year. Almost 70% percent of these firms are single plant firms. The NACE codes are given at the 4 digit level in main

[6] Nomenclature of Statistical Territorial Units, NUTS3K variable is missing for some firms and it is not appropriate to do analysis from agglomeration perspective due to representativeness issues.

[7] Plant level datasets include only wage bill, employment, turnover, industry codes and location of plant at the NUTS2K level. Using turnover shares, I created value added at the plant level.

[8] Sampling weights are provided by TURKSTAT.

industry dataset and 2 digit in the plant level dataset. Before 2009 the industry NACE codes are classified according to first revision.[9] After 2009, all of the NACE codes are classified into second revision in both datasets. I converted missing NACE Rev.1 codes to revision 2 by first using the conversion tables and then following the literature[10].

In the data cleaning process, I first dropped firms whose main activity are non-manufacturing. Also, firms with zero or negative employment, wage bill, value added etc. are dropped. I observed some abnormalities in the lower bound of the variables of interest regarding the sampling issues.[11] In order to express variables in real terms, deflation was made using industry specific deflators provided by TURKSTAT.[12] After constructing variables, I trimmed bottom and top 1% percent of variables of interest.

Throughout the analysis, I both used single and multi-plant firms and most of this multi-plant firms are located in the same region. Some industries and regions are represented by extremely low number of firms, thus I dropped these observations. [13] As a whole, our multi-plant firm sample employment levels cover almost 83% of manufacturing employment in Turkey in 2015. Also, note that the single-plant firms sample employment levels cover 50% percent of total manufacturing employment.

[9] Using the backcasting method TURKSTAT convert the Rev. 1 to Rev. 2, however, some firms industry codes left missing.

[10] Kalemli-Ozcan et al. (2015) explain how they convert Nace Rev. 1 codes to Rev. 2.

[11] Some firms are selected for the survey but cannot be reached. TURKSTAT provides imputation of the variables for these type of firms. But these imputations can have insensible values, so I got rid of these observations.

[12] There is no industry specific deflators provided by TURKSTAT for the NACE Rev.2 code of 33. Thus I use the deflator of the closest industry.

[13] I dropped 3 different regions (TRA1, TRA2, TRB2) and I also dropped Manufacture Of Tobacco Products, Coke And Refined Petroleum Products and Basic Pharmaceutical Products and Pharmaceutical Preparations due to representativeness issues. These industries together cover only 1% of manufacturing in 2015. Also, the regions I dropped compose 0.6% percent of manufacturing employment. in 2015. For other detailed coverage over regions and industries see tables A1 and A2 in Appendix A.

In order to calculate the monetary value for the firm level gap, we derive marginal product and marginal cost of each firm. Marginal product of each firm is calculated using the labor share of industries in their value added at the 2 digit Nace Rev.2 codes. Marginal cost is measured as the average wage for each firm, wage bill per employee. I used the difference between marginal product and marginal input price in my analysis as a firm level distortion. The intuition behind this methodology comes from perfect competition where the value of an input's marginal return should be equal to the marginal cost.

In addition to the Annual Industry and Service Statistics, I use Annual Trade Statistics to construct firm specific exchange rates for the economic concentration, firm level distortion and exchange rate shocks regression analyses. Annual Trade Statistics offers transactional level detailed information on firm's trade partners, trade volumes, and values. In this part, I match these two datasets by using firm unique IDs and year variable.[14] To be able to construct real exchange rates, I collect exchange rates and consumer price index (CPI) from both United Nations Conference on Trade and Development Statistics (UNCTADSTAT) and World Bank Development Indicators (WDI) databases.[15] Following the literature (Dai and Xu, 2017), I calculated export/import (EXFEER/IMFEER) firm specific exchange rates as follows:

$$\Delta EXFEER_{it} = \sum_{k}(EX_{ik,t-1}/\sum_{k}(EX_{ik,t-1})\Delta lne_{kt} \tag{1}$$

$$\Delta IMFEER_{it} = \sum_{k}(IM_{ik,t-1}/\sum_{k}(IM_{ik,t-1})\Delta lne_{kt} \tag{2}$$

[14]Note that Annual Trade Statistics do not provide any information at the plant level.

[15]Penn World Tables 9.0 do not provide values for the year 2015. Also, there are missing values for some countries.

The changes in country's real exchange rate are weighted with id-year-destination specific trade shares and aggregated to the firm-year level. In particular, e_{kt} denote the real exchange rate between Turkey and country k, expressed as units of country k's currency per unit of Turkish Lira. In other words, an increase in e_{kt} implies the appreciation of Turkish Lira against country k's currency. In a given year, weights represent the importance of export (import) of that specific country in the firm's total export (import) value. Note that, in order to avoid endogeneity lag share of these weights are used. After calculating the export and import specific exchange rates for each id-year group in Annual Trade Statistics, I aggregate these measures using import and export weights in firms total trade values in that year. Thus, firms who are actively both importer and exporter will be affected by the shocks of exchange rates due to offsetting effect of exporting activity in this case. When combined with Annual Industry and Service Statistics, firm specific exchange rate will be zero for the firms who do not participate in trade activities over time.

3.2 Descriptive statistics

After the cleaning process, the total numbers of observations are reduced to 279,923 for the multiplant analysis. 195,946 numbers of these observations of the whole sample are single plant firms. Also,133,421 number of them are declared to be exporters.[16] Figure 1 illustrates the composition of the dataset. The number of firms surveyed increased slightly each year. However, the share of exporters and single plant firms cover almost the same proportion of the sample over time.[17]

[16] Note that these numbers apply only to the multi-plant analysis, in single plant analysis part, number of observations reduced to 192,833 due to re-running the analysis separately.

[17] Share of exporters and single plant firms in the sample are around 45% and 66% respectively.

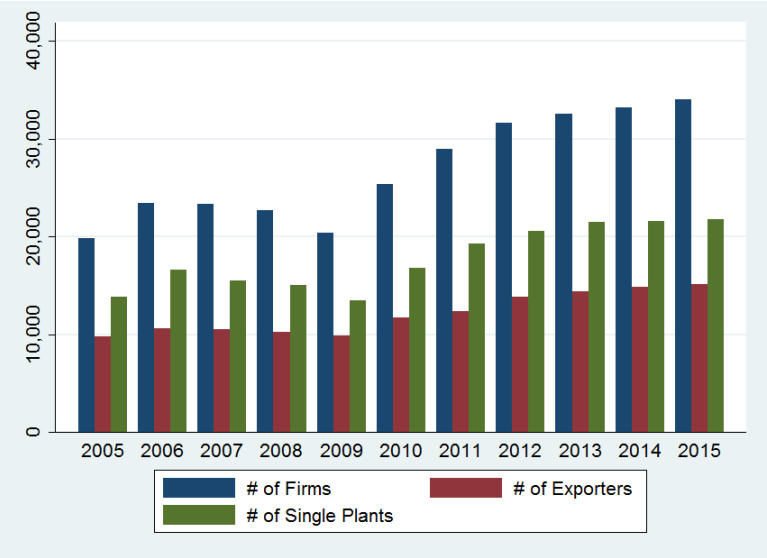

Figure 1. Dataset composition

Prior to moving the detailed analyses, the dataset is separated into two groups as low and high agglomeration areas depending on the employment level for the year 2015 [18]. Figure 2 shows that, as Combes et al. (2012) suggested, there is no sign of left truncation. In contrast, we can see that productivity distribution is right shifted in the areas where agglomeration is above the median level.

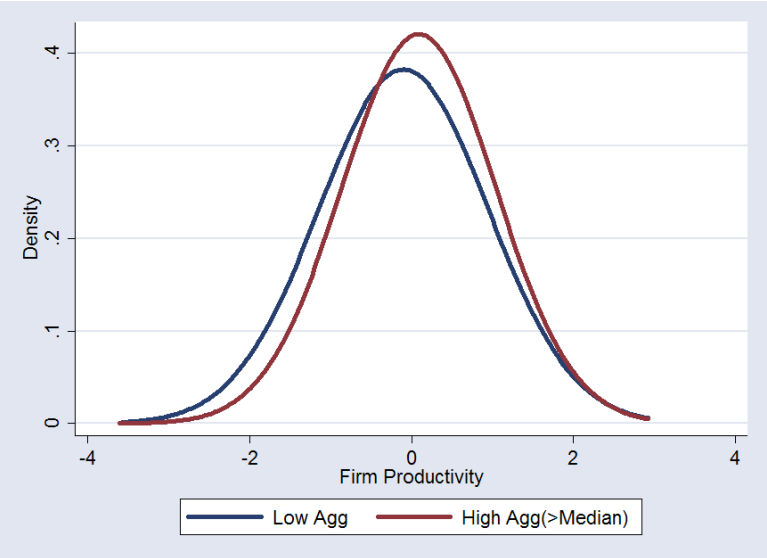

Figure 2. Urbanization and productivity

[18]The pattern observed in this distribution is robust using other years like the mid-year, 2010.

The original dataset is representative at 2 digit NACE Rev.2 and NUTS2K level of Turkey.[19]. In order to prevent bias and check the sample representativeness, I construct the coverage tables for the whole years of analysis for the single plant sample. I compare employment levels in my sample with the real values. The Table A1 and Table A2 in the Appendix A shows the coverage of the sample for single-plant firms' sample from regional and industry perspective for the year 2009. Overall, the sample dataset covers a high proportion of real employment levels both from regional and industry perspective.[20]

[19]It refers to 26 different regions of Turkey. But note that in my analysis I use 23 different regions.

[20]The coverage tables for the other years are available on request (2009-2015). Note that before 2009, TURKSTAT do not provide employment levels from a regional perspective. Table A3 in the Appendix A also gives summary details about the sample.

CHAPTER 4

THE ESTIMATION METHOD

For the industry level analysis, I calculate the standard Olley and Pakes (OP) covariance term between firm size and productivity at the regional level as follows;

$$OPCov_{szt} = \sum_i (\theta_{iszt} - \bar{\theta}_{szt})(\omega_{iszt} - \bar{\omega}_{szt}) \tag{3}$$

θ_{iszt} and ω_{iszt} represent labor share of a firm in that specific industry-region group and log labor firm-level productivity at time t, respectively. Also, bar over a variable indicates unweighted industry-region-year average. As it is used in Bartelsman et al. (2013), this measure basically captures allocative efficiency between size and productivity within industry. Thus, it measures the basic idea behind misallocation in quantitative terms, whether the more productive firms can allocate more resources.[21]

For the firm level analysis, following the Petrin and Sivasadan (2013), I calculated the gap between marginal product and the marginal cost.[22] After deflating all the variables of interest with industry level Producer Price Index[23], I calculate the marginal product as the multiplication of value added per worker with the industry specific time-invariant labor shares.[24]

$$VMP_{it}^{L} = \phi_{it}^{l} \frac{Y_{it}}{L_{it}} \tag{4}$$

[21] Note that for this analysis, I only kept single plant firms as in later parts examining the effect of agglomeration economies.

[22] Having already the capital stock values at the firm-level, they use Wooldridge (2009) method for the estimation.

[23] PPI values are taken from TURKSTAT at the 2 digit of NACE Rev.2 level.

[24] Since there is no asset level for firms, I need to calculate marginal product as value added per worker. Because capital estimation decreases the number of observations immensely, it is not useful for this analysis.

I calculated time-invariant industry specific labor shares as the share of wage bill in their value added levels from two digit industry tables that TURKSTAT provides.[25] After calculating the productivity level of each firm, I checked the productivity distribution over years.

Figure 3 shows that the productivity of Turkish firms increased and shifted to the right over time. Indeed, the average productivity of firm in 2005 was 2.4% lower than the average productivity observed in 2010. Even though this dispersion does not explain the pattern of firm level distortions, it gives a simple insight about the performances of the Turkish manufacturing firms over time.

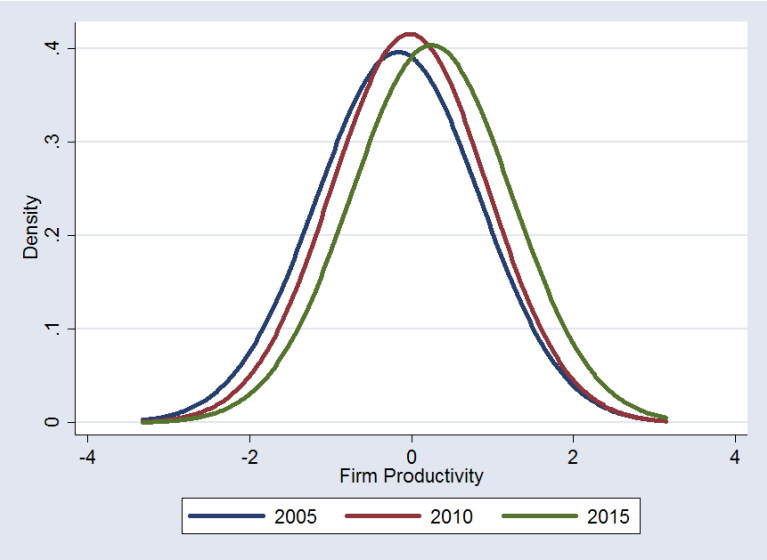

Figure 3. Manufacturing firms' productivity distribution

Secondly, the wage of a marginal worker is used as a marginal cost at the firm level as in Fontagné and Santoni (2018). Lastly, the value of absolute gap can be summarized as follows:

$$G_{it}^{L} = VMP_{it}^{L} - \omega_{it} \tag{5}$$

[25] Table 1 illustrates the labor input coefficients. Also, in the robustness part, I repeat the analyses with the industry labor shares derived from the sample.

G_{it}^{L} is the labor gap defined as the difference between marginal product and marginal cost at the firm level. Table 1 presents descriptive statistics for average Absolute Gap. Mean Absolute Labor gap in the following table for a particular sector in a specific year is constructed as follows;

$$Gap_s^{Abs} = \frac{\sum_{i \in s} |G_i^{abs}|}{N_s} \tag{6}$$

I also calculated Coefficient of Variation (CV) by dividing standard deviation of calculated gaps to their mean. It shows the estimated gap dispersion within industries. Overall, there is a high dispersion of estimated gaps in the whole dataset.

Table 1. Average Absolute Labor Gap by Sector–Years 2005–2015

			Gap^{Abs}	
Industry	Obs	Input coefficient	Mean	CV
Wood products	5373	0.328	3563.909	1.169
Basic metals	5373	0.347	4105.835	1.219
Printing and recording	5371	0.495	3541.775	1.296
Computer and electronics	1833	0.434	7536.586	0.938
Leather products	5138	0.520	2530.213	1.465
Other manufacturing	5207	0.455	5421.776	1.081
Other transport	3051	0.489	4704.597	1.267
Pharmaceutical	1184	0.563	14262.710	0.701
Electrical equipment	9618	0.425	3696.417	1.217
Fabricated metal	26284	0.460	3014.671	1.354
Food products	30714	0.455	4083.609	1.344
Wearing apparel	43563	0.585	2789.660	1.468
Beverages	1462	0.296	7518.688	0.893
Paper products	5839	0.387	3815.194	1.155
Chemicals	10074	0.334	6534.603	1.049
Machinery and equipment	25125	0.423	3485.226	1.252
Repair and Installation of machinery	4302	0.548	3051.531	1.441
Nonmetallic products	20003	0.372	3784.561	1.322
Furniture	15125	0.563	2233.279	1.686
Motor vehicles	6232	0.422	4640.542	1.030
Rubber and plastic	18023	0.406	3669.396	1.262
Textiles	31029	0.421	3218.959	1.274
Overall	279923	0.457	3616.948	1.317

Total number of observations are 279,923 for the 2005-2015 period. Also the number of different firms equal to 80,715. Even though gap calculation method differs from their estimation, I found that the gap is especially higher for the some

industries like Beverages, Pharmaceutical, Chemicals and Computer and electronics as in Fontagné and Santoni (2018). Thus, this might imply that firms in that sector have relatively higher distortions on average.

In Table 2, estimated gaps are divided according to their sign. It can be seen that almost 39% of the whole sample have a positive gap. And the overall absolute gap range from almost 400 to 8000 Turkish Lira over the whole period.

Table 2. Labor Gap Decomposition

	$\lvert G_{it} \rvert$	$G^L_{it} < 0$	$G^L_{it} > 0$
# of Obs	279923	171493	108430
Mean	3366.555	2223.456	5174.482
sd	4802.001	2398.442	6715.393
p10	407.449	448.1272	352.0715
p50	1867.461	1689.375	2621.93
p90	7558.61	4264.702	13661.64

Estimated gaps present a deviation measure from the optimal decision at the firm level. Thus, these deviations can be the reflection of adjustment costs, markups, or policy distortions. Instead of separating these effects I first look at the evolution of gaps over time. Then I check whether employment concentration level has any implication on these gaps. And finally, I look at the mediating role of labor market thickness to the exchange rate shocks.

CHAPTER 5

RESULTS

5.1 Industry level allocative efficiency and agglomeration economies

This part examines the effect of labor market thickness on the industry level allocative efficiency measured by regional OP covariance term. Following analyses which highlight the importance of economic concentration of an area, this part investigates possible implications of economic concentration on labor misallocation.[26]

$$OPCov_{szt} = \beta_1 ln(Location_{zst}) + \beta X_{szt} + \tau_{zs} + \tau_{st} + \varepsilon_{szt} \tag{7}$$

Dependent variable $OPCov_{szt}$ refers to sector-region-year level covariance between size and labor productivity. It measures within industry-region allocative efficiency. $ln(Location_{zst})$ is used as a proxy for economic concentration. I also add sector-region-year specific industry controls including share of exporters and competition index derived from turnover shares.

Table 3 shows the results of the regression analysis. Note that all of the regressions below includes sector-year and sector-region fixed effects.[27] Results suggest that doubling the degree of employment in that region-sector group will increase the covariance term by 0.09. Although it is not completely meaningful from the quantitative perspective, positive effect of economic concentration OP covariance term linked to better allocation of resources (labor) across firms in an industry-region group. In other words, it can be said that in denser areas within industry-region

[26] See Behrens et al. (2014), Combes et al.(2012), Fontagné and Santoni (2018).

[27] The results are robust using sector-region fixed effects with year dummies. All these tables can be found in APPENDIX B.

misallocation is lower. Many dimensions of agglomeration economies might be associated with this outcome like technology and productivity spillovers or matching channel between firm and workers due to large employment pool in that sector-region group.

Table 3. Economic Concentration and Industry Level Allocation

	$OPCov_{szt}$		
	(1)	(2)	(3)
ln($Location_{zst}$)	0.0580***	0.0946***	0.0946***
	(0.00869)	(0.00819)	(0.00854)
Industry-Region & Ind.-Year	Yes	Yes	Yes
Industry Controls		Yes	Yes
Cluster Level	Region	Region	Region & Ind.-Year
Observations	3,693	3,693	3,693
R-squared	0.625	0.692	0.692

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.2 Progression of absolute gap over time

This part mainly aims to investigate the overall pattern of gap over time periods by controlling firm fixed effects. The estimated equation in the first part is given as:

$$G_{it}^{abs} = \alpha_0 + \gamma_1 + \gamma_2 + \gamma_3 + \Gamma_{it}\beta + \zeta_i + \varepsilon_{it} \tag{8}$$

Our dependent variable is absolute labor gap defined in thousand terms while independent variables at the firm level include period dummies and size (turnover) dummies. Turnover dummies are controlled to see whether firm's size has significant power on the observed absolute gap. I also add export status of the firm along with competition level of industry. In order to control industry level competition, I add a control variable called $comp_{st}$. Basically, it is the reverse of Herfindahl-Hirschmann index and used as a proxy for market concentration level. Lastly, firm fixed effects are controlled.

Table 4 presents baseline estimations by suggesting that period dummies are always significant. The absolute labor gap is increasing over time with respect to reference period, 2005-2009. Indeed, the gap between marginal product and marginal cost was 746 Turkish Lira higher in 2013-2015 when compared to 2005-2009 period. Also, with respect to the fifth quintile, I found that while the absolute gap is lower at the third and fourth quintile, also firms at the first quintile have higher absolute gap on average. And I could not find significant effect at the second quintile. These results can be attributed to more than one possible explanation. Since estimated gap might include adjustment costs, markups, or policy distortions one of the possible explanation can be related to the size dependent policies. As Garicano et al. (2016) suggested, size contingent labor regulations can affect bigger firms more than small firms. Also, firms who have higher turnover values are more likely to have higher markups. Since all of these effects might have various or even opposite implications on different size of firms, it makes the precise interpretation very hard. In addition, I found that in our dataset the gap between marginal product and marginal cost is higher for exporter firms on average. Even though exporter firms are more productive on average when compared to firms who are not in trade activity, as asserted above, the estimated gap may not necessarily be an efficiency measure but might be compound of many other firm level idiosyncratic elements. Indeed, Bellone et al. (2016) found that exporter firms have higher level of markups. Therefore, having a higher level markup can lead to relatively high level absolute gap for the exporter firms. I also found that $Comp_{st}$ affects labor gap negatively. This result is in line with Bellone et al. (2016) outcomes which suggest that competition is negatively correlated with firm level markups.

Table 4. Labor Gap with Multiplant Firms (in thousands)

	Absolute Gap			
	(1)	(2)	(3)	(4)
2009-2011	0.216***	0.211***	0.210***	0.202***
	(0.0672)	(0.0666)	(0.0666)	(0.0679)
2012-2013	0.469***	0.456***	0.453***	0.472***
	(0.0741)	(0.0734)	(0.0733)	(0.0778)
2014-2015	0.746***	0.731***	0.726***	0.756***
	(0.0744)	(0.0744)	(0.0745)	(0.0822)
1^{st} Quintile		-0.114	-0.104	-0.106
		(0.118)	(0.118)	(0.118)
2^{st} Quintile		-0.249**	-0.240**	-0.241**
		(0.117)	(0.117)	(0.117)
3^{st} Quintile		-0.379***	-0.373***	-0.374***
		(0.107)	(0.107)	(0.107)
4^{st} Quintile		-0.270***	-0.268***	-0.268***
		(0.0875)	(0.0874)	(0.0874)
Exp_{it}			0.166***	0.166***
			(0.0381)	(0.0382)
$Comp_{st}$				-0.129*
				(0.0683)
Fixed Effects	Firm	Firm	Firm	Firm
Cluster level	Firm & Ind.-Reg.	Firm & Ind.-Reg.	Firm & Ind.-Reg.	Firm & Ind.-Reg.
Observations	279,923	279,923	279,923	279,923
R-squared	0.526	0.526	0.526	0.526

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 4 shows that the average absolute labor gap pattern for its real positive and negative values over time conditional on firm characteristics. Both of the real positive and negative gap increasing over time. The value and the volatility of absolute gap is higher for the firms who show positive real gap.

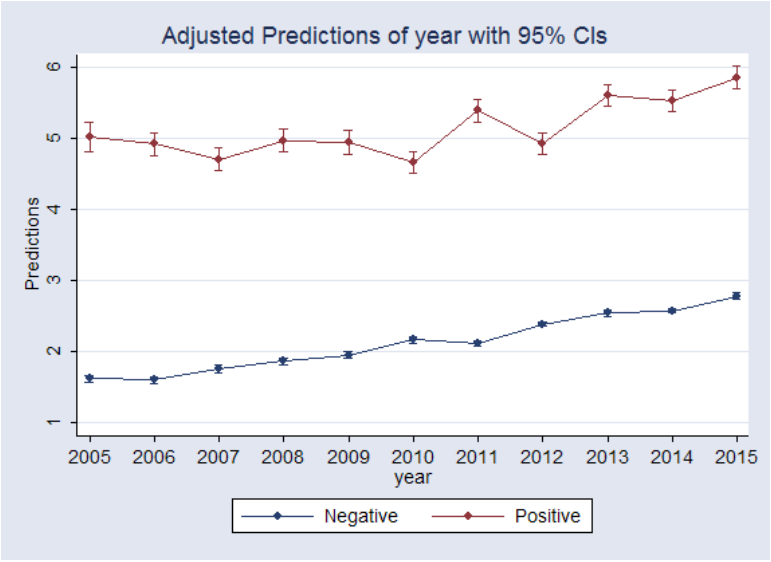

Figure 4. Average labor gap conditional on firm characteristics

I also repeat the analysis with different specifications: I use the labor shares that I derived from the sample, keep only the firms who have more than 49 employees, and use time invariant controls. Table 5 shows that results are robust using different specifications.

Table 5. Robustness of Multi-Plant Firm Analysis (in thousands)

	Absolute Gap		
	Time-Invariant Turnover Dummies	Employ $\geq$ 49	Labor Share from Sample
2009-2011	0.202***	0.212**	0.185**
	(0.067)	(0.0827)	(0.0769)
2012-2013	0.472***	0.308***	0.372***
	(0.078)	(0.0964)	(0.0905)
2014-2015	0.755***	0.517***	0.703***
	(0.082)	(0.100)	(0.0920)
Fixed Effects	Firm	Firm	Firm
Cluster level	Firm & Ind.-Reg.	Firm & Ind.-Reg.	Firm & Ind.-Reg.
Observations	279,923	103,106	279,923
R-squared	0.547	0.614	0.547

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In order to control multiplant firm effects and prove that my results are not driven by sample selection, I repeat the analysis only for single plant firms. As suggested in the table below, Table 6, I observed that period dummies still significant and substantial. Turnover dummies in this part are always significant and negative, suggesting that firms who have higher turnover will have higher absolute gaps. Similar to multiplant analysis, export dummy affects absolute gap positively and competition measure is negative but insignificant.

Table 6. Labor Gap with Single Plant Firms (in thousands)

	Absolute Gap			
	(1)	(2)	(3)	(4)
2009-2011	0.207***	0.192***	0.192***	0.194***
	(0.0355)	(0.0342)	(0.0343)	(0.0348)
2012-2013	0.478***	0.436***	0.435***	0.441***
	(0.0478)	(0.0470)	(0.0470)	(0.0492)
2014-2015	0.686***	0.639***	0.637***	0.646***
	(0.0473)	(0.0469)	(0.0469)	(0.0510)
1^{st} Quintile		-0.370***	-0.361***	-0.362***
		(0.0613)	(0.0610)	(0.0609)
2^{st} Quintile		-0.581***	-0.574***	-0.576***
		(0.0556)	(0.0553)	(0.0551)
3^{st} Quintile		-0.566***	-0.561***	-0.562***
		(0.0501)	(0.0498)	(0.0495)
4^{st} Quintile		-0.349***	-0.347***	-0.347***
		(0.0411)	(0.0410)	(0.0409)
Exp_{it}			0.0678***	0.0679***
			(0.0230)	(0.0229)
$Comp_{st}$				-0.0196
				(0.0310)
Fixed Effects	Firm	Firm	Firms	Firm
Cluster level	Firm & Ind.-Reg.	Firm & Ind.-Reg.	Firm & Ind.-Reg.	Firm & Ind.-Reg.
Observations	192,833	192,833	192,833	192,833
R-squared	0.599	0.601	0.601	0.601

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.3 Firm level distortions and labor market thickness

In this part, I focused on the effect of labor market thickness on the gap between marginal product and marginal cost. Results in this part will basically explain the mediating role of agglomeration economies to the firm level distortions.[28] In order to assess this relationship, I run the following equation.

$$ln(G_{it}^{abs}) = \beta_1 ln(Location_{zst}) + \Gamma_{it}\beta + X_{zst}\beta + \tau_{zs} + \tau_{st} + \varepsilon_{it} \tag{9}$$

Apart from the main independent variable, some controls at the firm and industry level are added. Firm controls include size and negative gap dummies while industry dummies cover average productivity of the sectors and share of exporters at the region-year-industry level. Furthermore, industry-year fixed to control sector

[28]Note that for this analysis, I only kept single plant firms when examining the effect of agglomeration economies on firm level distortions.

specific effects. Industry-region fixed effects are also added to control time invariant pattern of the regional labor market in that sector. The empirical analysis in this part uses only single plant firms since multiplant firms can distort the results. In Table 7, a summary table of the sample is given.

Table 7. Descriptive Statistics of Single Plant Sample

	Baseline Sample		Feer Sample		
	Ln(Absolute Gap)	ln(Location)	Ln(Absolute Gap)	ln(Location)	Feer
Observation	192,833	192,833	187,430	187,430	187,430
Mean	0.452	9.322	0.449	9.298	-0.001
Sd	1.042	1.591	1.040	1.593	0.033
p10	-0.941	7.214	-0.944	7.188	-0.032
p50	0.580	9.442	0.577	9.409	0.000
p90	1.691	11.841	1.685	11.753	0.029

Note: Note that Feer refers to firm specific exchange rate. Absolute Gaps are in thousands.

Table 8 represents Baseline OLS results. In column (1), only firm controls are added. Columns (2) and (3) uses both firm and industry controls with different clustering levels. In the light of the empirical results, even 1% change in regional employment, agglomeration, will negatively affect log of the absolute gap around 0.03% percentage. In other words, the gap between marginal product and cost can decrease by 3% if labor market thickness increases by double.

Table 8. Economic Concentration and Firm Level Distortions

	Ln Absolute Gap		
	(1)	(2)	(3)
ln($Location_{zst}$)	-0.0282***	-0.0323***	-0.0323***
	(0.00820)	(0.00845)	(0.00901)
Industry-Region & Industry-Year	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Industry Controls		Yes	Yes
Cluster Level	Region	Region	Region & Ind.-Year
Observations	192,833	192,833	192,833
R-squared	0.095	0.095	0.095

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In order to control sample selection and industry classification change, I ran the same regressions for the balanced sample, a sample including 2009-2015 and

sample with industry shares derived from the dataset. The corresponding tables are given in Appendix B.

5.4 Firm level distortions, labor market thickness and exchange rate shocks

The aim of this part is investigating the mediating role of agglomeration economies on firm level behaviour. The motivation behind this part assumes that firms are less responsive to the exogenous shocks when they are located in an agglomerated area/region due to larger employment pool. In order to empirically test this idea, I observe the response of firm's when they expose to supply/demand shifter component like firm specific exchange rate changes.

In addition to controls in the baseline part above, this part uses exchange rate changes and its interaction with location measure.

$$ln(G_{it}^{abs}) = \beta_1 ln(Location_{zst}) + \beta_2 Feer_{it} + \beta_3 Feer_{it} ln(Location_{zst}) + \Gamma_{it}\beta + X_{zst}\beta + \tau_{zs} + \tau_{st} + \varepsilon_{it} \quad (10)$$

I construct firm specific exchage (Feer) at the id year level. The firm specific exchange rate is calculated using the whole trade dataset apart from some countries where exchange or inflation rates are missing and free zones.[29] The descriptive table for this part is given above. In detail, firm specific exchange rate is 0 for the firms who are not in trade activity.[30] Also, since some firms are not surveyed in every year, I need to keep the firms who are observed in the industry survey dataset. Since the dataset composition will be affected by this selection, I repeat baseline regressions

[29] Somalia, Ceuta, Palau, Nauru and Pitcairn are some the countries that I dropped when I calculate feer exchange rates. All of the trade partners dropped covered only 5% percent of the whole trade values for the sample years.

[30] For detailed information on the construction of Firm Specific Exchange rate see Chapter 2.

with this sample and found slightly less but still significant effects. These results are given in Table 9.

Table 9. Economic Concentration and Firm Level Distortions with New Sample

	Ln Absolute Gap		
	(1)	(2)	(3)
ln($Location_{zst}$)	-0.0249***	-0.0296***	-0.0296***
	(0.00830)	(0.00840)	(0.00914)
Industry-Region & Industry-Year FE	Yes	Yes	Yes
Firm Controls		Yes	Yes
Industry Controls		Yes	Yes
Cluster level	Region	Region	Region &Ind.-Year
Observations	187,430	187,430	187,430
R-squared	0.096	0.096	0.096

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10 shows the results of regressions with the firm specific exchange rate. As it can be seen from above that firm specific exchange rate has a negative effect on log of the absolute gap. It suggests that firms respond to exchange rate shocks (defined as appreciation) by decreasing their absolute gap. Also, its interaction with the log of location has a positive coefficient which may imply that firms who are in denser areas are less responsive to these exchange rate shocks. This results can be the outcome of many different things. One of the explanation, as Fontagné and Santoni (2018) suggested could be matching mechanism in denser areas. Apart from matching, firms might basically benefit from internal labor market thickness. In addition, learning channel (technology spillovers) might lead to such an outcome.

Table 10. Economic Concentration, Firm Level Distortions and Exchange Rate Shocks

	Ln Absolute Gap			
	(1)	(2)	(3)	(4)
ln($Location_{zst}$)	-0.0254***	-0.0301***	-0.0299***	-0.0299***
	(0.00844)	(0.00857)	(0.00856)	(0.00928)
Feer	-0.177***	-0.170***	-0.723**	-0.723**
	(0.0484)	(0.0468)	(0.303)	(0.304)
Feer#ln($Location_{zst}$)			0.0587*	0.0587**
			(0.0288)	(0.0282)
Ind-Reg & Ind-Year FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Industry Controls		Yes	Yes	Yes
Cluster level	Region	Region	Region	Region& Ind.-Year
Observations	187,430	187,430	187,430	187,430
R-squared	0.096	0.097	0.097	0.097

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

CHAPTER 6

CONCLUSION

Over the last decade, misallocation was regarded as the most prominent factor explaining the productivity differences across countries. Since it offers high level of potential gains in terms of productivity, misallocation became especially important for developing countries. Indeed, one of the developing countries Turkey has experienced high growth levels at the beginning of the 2000s along with substantial levels of resource allocation inefficiency in the manufacturing sector. Regarding the positive effect of agglomeration economies on productivity distribution, in this paper, I developed a link between economic concentration and misallocation for the manufacturing firms in Turkey. In order to test this idea, I used Olley and Pakes covariance term at the regional level and suggested that large employment pool in an area boosts the effective allocation of labor. Then, I focused on firm-level distortions and calculate the monetary value of distortions by using the gap between marginal input and marginal cost of labor. I found out that doubling the degree of employment level in that particular sector-region group can reduce firm level distortions by 3%. Finally, in order to assess the effect of short-run fluctuations to firm level reactions, I expanded this analysis by calculating the firm specific exchange rates. My results suggest that firms located in denser areas are less responsive to the exogenous exchange rate shocks thanks to mediating role of agglomeration economies which includes sharing, matching or learning channels.

APPENDIX A

SAMPLE COVERAGE

Table A1. Region Coverage for 2009

Region	Employment Real	Employment Sample	Share
TR10	809604	461918	0.571
TR21	99708	17978	0.180
TR22	32928	12822	0.389
TR31	169977	91677	0.539
TR32	99873	56488	0.566
TR33	82849	40943	0.494
TR41	246120	120951	0.491
TR42	200531	85112	0.424
TR51	148386	79996	0.539
TR52	66824	28480	0.426
TR61	45733	19071	0.417
TR62	62066	24380	0.393
TR63	61069	26695	0.437
TR71	31190	10898	0.349
TR72	66174	30427	0.460
TR81	37181	10368	0.279
TR82	14216	5831	0.410
TR83	50345	19977	0.397
TR90	45807	16876	0.368
TRB1	29109	10692	0.367
TRC1	72078	36549	0.507
TRC2	17524	8052	0.459
TRC3	8437	2291	0.272
Total	2497729	1218472	0.488

Table A2. Industry Coverage for 2009

NACE Rev.2	Employment Real	Employment Sample	Share
10	328281	128657	0.392
11	11580	3876	0.335
13	283513	141263	0.498
14	379060	204404	0.539
15	43680	19910	0.456
16	65993	24413	0.370
17	39290	19017	0.484
18	52934	33384	0.631
20	56963	20903	0.367
22	144049	82911	0.576
23	154569	68395	0.442
24	90721	32713	0.361
25	225666	134257	0.595
26	18368	7763	0.423
27	101909	46579	0.457
28	132857	77931	0.587
29	125075	53081	0.424
30	34516	15303	0.443
31	131073	58407	0.446
32	45155	24305	0.538
33	32477	21000	0.647
Total	2497729	1218472	0.488

Table A3. Summary Table for the Sample

	Employment	Turnover	Valueadded	Ln Productivity
# of Obs	279923	279923	279923	279923
Mean	93.041	11801.440	2354.837	9.599
sd	221.960	75162.580	14131.240	0 .732
p10	21	584.275	187.638	8.776
p50	41	2788.313	577.116	9.493
p90	185	19750.300	3823.695	10.600

Number of different firms equal to 80,715. Turnover and Valueadded values are in thousands and in terms of initial year.

APPENDIX B

ROBUSTNESS CHECKS

Table B1. Economic Concentration and Industry Level Allocation with Industry-Year & Region Fixed Effects

	$OPCov_{szt}$		
	(1)	(2)	(3)
ln($Location_{zst}$)	0.0651***	0.122***	0.122***
	(0.0105)	(0.0107)	(0.0111)
Industry-Year & Region	Yes	Yes	Yes
Industry Controls		Yes	Yes
Cluster Level	Region	Region	Region & Ind.-Year
Observations	3,693	3,693	3,693
R-squared	0.285	0.481	0.481

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B2. Single Plant Analysis Using Labor Input Coefficients from Sample

	Ln Absolute Gap		
	(1)	(2)	(3)
ln($Location_{zst}$)	-0.0222**	-0.0319***	-0.0319***
	(0.00956)	(0.00673)	(0.00863)
Industry-Region & Industry-Year FE	Yes	Yes	Yes
Cluster Level	Region	Region	Region & Ind.-Year
Firm Controls	Yes	Yes	Yes
Industry Controls		Yes	Yes
Observations	192,837	192,837	192,837
R-squared	0.191	0.193	0.193

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B3. Single Plant Analysis Using 2009-2015

	Ln Absolute Gap		
	(1)	(2)	(3)
ln($Location_{zst}$)	-0.0425***	-0.0443***	-0.0443**
	(0.0131)	(0.0123)	(0.0143)
Industry-Region & Industry-Year FE	Yes	Yes	Yes
Cluster Level	Region	Region	Region & Ind.-Year
Firm Controls	Yes	Yes	Yes
Industry Controls		Yes	Yes
Observations	131,609	131,609	131,609
R-squared	0.098	0.099	0.099

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B4. Single Plant Analysis Using Balanced Sample

	Ln Absolute Gap		
	(1)	(2)	(3)
ln($Location_{zst}$)	-0.165**	-0.161**	-0.161**
	(0.0602)	(0.0584)	(0.0594)
Industry-Region & Industry-Year FE	Yes	Yes	Yes
Cluster Level	Region	Region	Region& Ind.-Year
Firm Controls	Yes	Yes	Yes
Industry Controls		Yes	Yes
Observations	19,976	19,976	19,976
R-squared	0.111	0.112	0.112

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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