

Bagir, Yusuf Kenan

**Article**

## Impact of the Syrian refugee influx on Turkish native workers: An ethnic enclave approach

Central Bank Review (CBR)

**Provided in Cooperation with:**

Central Bank of The Republic of Turkey, Ankara

*Suggested Citation:* Bagir, Yusuf Kenan (2018) : Impact of the Syrian refugee influx on Turkish native workers: An ethnic enclave approach, Central Bank Review (CBR), ISSN 1303-0701, Elsevier, Amsterdam, Vol. 18, Iss. 4, pp. 129-147, <https://doi.org/10.1016/j.cbrev.2018.11.001>

This Version is available at:

<https://hdl.handle.net/10419/217324>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

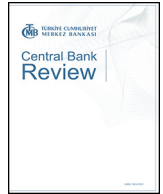
*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<https://creativecommons.org/licenses/by-nc-nd/4.0/>



# Impact of the Syrian refugee influx on Turkish native workers: An ethnic enclave approach<sup>☆</sup>

Yusuf Kenan Bağır

Structural Economic Research Department, Central Bank of the Republic of Turkey, İstiklal Cad. No:10, 06100, Ulus, Ankara, Turkey



## ARTICLE INFO

### Article history:

Received 26 October 2018  
Received in revised form  
15 November 2018  
Accepted 15 November 2018  
Available online 27 November 2018

### JEL classification:

F22  
J15

### Keywords:

International migration  
Economics of minorities  
Races  
Indigenous peoples  
Immigrants

## ABSTRACT

Turkey received about 2.7 million Syrian refugees between 2011 and 2015. This paper examines the causal impact of this influx on the Turkish natives' labor market outcomes using the micro level annual Household Labor Force Surveys. The migration impact is analyzed in two distinct categories considering the motives behind the migration decision. The initial migration to the border regions is defined as the primary migration and a standard difference in differences strategy is employed to estimate the labor market impacts in those regions since the initial flow to the border regions was completely exogenous. The migration from the primary regions towards the inner regions, on the other hand, is subject to endogenous selection. Hence, I defined it as the secondary migration and developed an instrumental variables estimation method to address the selection bias following the Card (2009)'s ethnic enclave approach. I found statistically significant negative employment and wage effects on the low-skilled and less-experienced individuals in the primary migration analysis. The decline in the wages of informal workers is the main contributor of the negative wage effects. Secondary migration has no impact on the employment but there are statistically significant negative wage effects on the low-skilled and less-experienced workers.

© 2018 Central Bank of The Republic of Turkey. Production and hosting by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

## 1. Introduction

Turkey has been enormously affected by the Syrian Refugee influx as it has the longest continental border with Syria. Following an open border policy for those victims of the Civil War, the country received more than 2.7 million Syrian refugees in just 4 years (2011–2015). In this study, I aim to contribute to the literature on the labor market impacts of the immigrants by analyzing the labor market outcomes of this massive refugee influx from Syria to Turkey.

Several studies asking the same question have been published in the academic journals or as working papers very recently. Among those [Akgunduz, Berk, and Hassink \(2015\)](#) investigate the impact on several outcomes including the food and housing prices, employment rates and internal migration patterns through a difference-in-differences estimation method by using the aggregated province level data. They find no considerable negative

impact on the employment level of natives in the region while the food and housing inflation gets disproportionately larger. [Ceritoglu, Yunculer, Torun, and Tumen \(2015\)](#) focus more specifically on the labor market outcomes including wages by making use of the individual level Household Labor Force Survey data. Following a similar difference-in-differences strategy with a narrower comparison group, the authors find considerable negative employment effects but no wage effects. Lastly, a working paper by [Del Carpio and Wagner \(2015\)](#) follows a more sophisticated strategy than the typical difference-in-differences estimation by measuring the impact at national level and instrumenting the refugee intensity across regions with geographical distance from the conflict area in Syria. Authors argue that the refugee influx led to the displacement of informal, low-educated female Turkish workers and impacted average wages positively as a result of the low-skilled natives' displacement from the job market and the remaining natives' occupational upgrading.

In this study, I follow a different strategy from the previous studies in several ways.

Firstly, I analyze the Syrian refugee influx in two separate categories, which are determined according to the characteristics of the movement. I defined the initial migration from Syria towards

<sup>☆</sup> The views expressed here are of the author and do not necessarily reflect those of the Central Bank of the Republic of Turkey.

E-mail address: [yusufkenan.bagir@tcmb.gov.tr](mailto:yusufkenan.bagir@tcmb.gov.tr).

Peer review under responsibility of the Central Bank of the Republic of Turkey.

the border regions of Turkey as the primary migration (exogenous) and the migration flow from these border regions towards the inner regions of Turkey as the secondary migration (endogenous). Because the primary migration is an unambiguous exogenous shock, a standard difference-in-differences estimation strategy is employed to estimate the primary migration effects as in [Akgunduz et al. \(2015\)](#) and [Ceritoglu et al. \(2015\)](#), with a different strategy in the formation of comparison group. The comparison group is synthetically constructed from the regions that did not receive many refugees but represent the highest positive historical correlation with the treatment regions in terms of labor force participation, employment, and average wages.

For the secondary migration analysis, I developed an instrumental variables (IV) approach to address the possible selection bias following the [David Card's \(2009\)](#) ethnic enclave design. Pre-existing migration pattern of Turkish natives from the primary migration regions is used as an instrument for the Syrian refugees' distribution across the country. The assumption is that the Syrian refugees share a common cultural and ethnical background with Turkish natives living in the Syrian border regions thus they are very likely to follow the migration path of these Turkish natives. First stage estimates confirm this assumption showing that the ethnic enclave variable is highly positively correlated with the destination choice of refugees. Likewise, the IV estimates are consistently larger in magnitude than the OLS estimates, which is expected from a valid instrument addressing the problem of a downward bias (refugees may be migrating into the regions that have better economic outlook).

Secondly, I use the recently available Household Labor Force Survey data (2015) and take 2012 as the pre-treatment year rather than 2011 and 2010 in the previous studies. The conflict in Syria has affected the regional labor market through two main channels. The first channel is the refugee induced increase in labor supply (the question of interest in this study) and the second is the possible contraction in regional economy because of the War in Syria. My objective in considering 2012 as the pretreatment year is to disentangle these two competing effects and narrow the treatment period. The timeline of the number of Syrian refugees and a field survey with refugees ([AFAD, 2013](#)) also imply that 2012 is more relevant in terms of the presence of Syrians in the job market.

Finally, I use the confidential immigrant registration data to obtain the distribution of the refugees across regions whereas the previous studies rely on approximate numbers provided by some national news agencies.

In this study, I basically aim to test the theoretical predictions of the standard models with separable capital input and single output, on which many studies are based including [Card \(2001\)](#), [Borjas \(2003\)](#), and [Ottaviano and Peri \(2012\)](#). These models primarily assume that skilled and unskilled workers are two separate production inputs; capital supply is perfectly elastic; and skilled and unskilled labor supplies are perfectly inelastic. An immigration induced labor supply shock under these assumptions generates no change on the employment; however, we may experience differential impacts on native workers' wages depending on the skill composition of immigrants. If the skill composition of immigrants is unskilled biased, unskilled (skilled) labor wages are predicted to decline (rise). The opposite is predicted if the skill composition of immigrants is skilled-biased. The model predicts no impact at all if the skill composition of new workers is exactly the same with natives. In all three cases, total output increases unambiguously. When the elastic capital assumption is relaxed, then we may observe a decline in the wages of both labor types ([Lewis, 2012](#)). A big majority of existing empirical studies generate contrasting results with these predictions and hardly finds negative wage effects of migration ([Glitz, 2012](#); [Dustmann et al, 2013, 2017](#)).

My findings in this study somewhat differ from the previous empirical analyses for both Turkey and other countries but largely in line with the theoretical predictions. My results imply consistent and statistically significant negative employment effect on low-skilled and less-experienced individuals in the primary migration regions of Turkey. Accordingly, the probability of employment declined by 3.2 (4.2) percentage points among the male (female) individuals with less than 8 years of education in the treatment regions. These results may seem to be much larger than the findings of previous literature; however, they must be interpreted considering the size of the migration shock in the case of Turkey (about 10% of the population in the treatment regions). Analysis for the secondary migration regions at the national level did not generate a statistically significant negative employment effect. Contrasting results between the primary migration regions and the secondary migration regions can be interpreted as that the economy is able to absorb the additional labor supply through the capital adjustment mechanism when the migration influx is at a reasonable level.

Wage estimations represented a similar pattern for the most vulnerable groups but the impact was also visible at the secondary migration areas. Overall male real hourly wages declined by 7.9% (not significant for females) in the treatment regions. The impact was much larger on the unskilled, less-experienced individuals. Disaggregation by sectors and firm size showed that the individuals working in those sectors that are more prone to informal employment are the ones most negatively affected. A further disaggregation between formal and informal employees, carried out in order to control for the possible heterogeneous treatment effects on informal employees, revealed that the decline in the wages of informal workers is the main contributor of the negative wage effects.

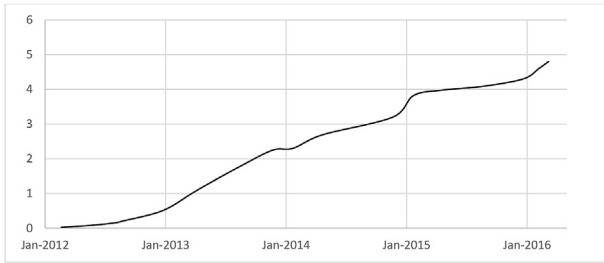
In the secondary migration regions, the overall wage impact for males (females) is found to be around 1.4% (0.8%) in response to a one-unit increase in the ratio of migrants to the regional population. The impact was heterogeneous across various skill, age, and sector groups, here as well. Accordingly, a one-unit increase in the migration ratio led to 1.4% (2%) decline in the wages of male workers with less than 5 (5–8) years of education while the impact was not statistically significant among the individuals with higher education. Similarly, the negative impact was statistically significant only among younger individuals and those individuals working in the small firms.

The paper proceeds with a short background of the Syrian refugee crisis and its impacts on Turkey in section 2. Section 3 and 4 cover the analysis of the primary migration and secondary migration impacts respectively. The paper ends with concluding statements.

## 2. Background of the Syrian Refugee crisis

The nationwide uprising in Syria started in March 2011 following the Arab Spring movement across the Middle Eastern countries. Protestors were demanding the release of political prisoners initially but the Syrian government responded with violence. As protests widened across the country and the government response became more violent, it turned out to be a civil war as of May 2011. Intensifying clashes between the government forces and anti-regime groups especially in the Northern Syria gave rise to the first refugee crisis in June 2011 as 10,000 Syrian refugees fled into Turkey (Timeline: [Key moments in Syrian crisis](#), <http://www.bbc.com/news/world-middle-east-18891150>).

Since then, more than 4.8 million people fled to the neighboring countries including Turkey according to the United Nations estimates ([UNOCHA, 2016](#)). [Fig. 1](#) represents the growth trend of the number of Syrian refugees over time. While the numbers were at



**Fig. 1.** The total number of Syrian refugees over time (Millions).  
Source: United Nations (OCHA)

reasonable levels until 2013, the graph shows that the total amount rised sharply after early 2013.

Having the longest continental border with Syria, Turkey is one of the countries that have been seriously affected from the Syrian Refugee Crisis together with Jordan and Lebanon. Turkey declared that it would have followed an “open border” policy for all the victims of the conflict since the start of the Civil War. The country responded to the refugee influx efficiently by rapidly building refugee camps. However; as the numbers grew beyond the capacity of the camps, the Turkish government had to relax the controls and allow refugees entering into the inner regions as well. According to the Ministry of Interior in Turkey, the total number of registered refugees reached 2.747 million as of March 2015 and only 272 thousands of those were located in refugee camps while the rest migrated into the country.

Turkish government established a specific agency under the Ministry of Interior (Directorate General of Migration Management) for the administration of the immigrants and passed a law that granted a temporary protection status for the Syrian Refugees in April 2013. A biometric registration is required in order to be eligible for certain social benefits such as free education and health protection. This requirement encouraged Syrian migrants to apply for the temporary protection status thereby made the counting of Syrian refugees in Turkey more reliable.

Fig. 2 shows the spread of Syrian refugees across 26 statistical regions in Turkey as of October 2015 according to the official registration data. Three regions that are closest to the conflict areas have the highest density of refugees with 8%–14% of the regional native population. Regions that have borders to Syria but further from the conflict area have a density of 5%–6%. Those areas shaded with light color has relatively smaller densities ranging from 1% to 2.5%. And finally, not shaded areas represent the regions with less than 1% density.



**Fig. 2.** Ratio of refugees to the regional population (October 2015).  
Source: Directorate General of Migration Management, Ministry of Interior, Turkey

The distribution of refugees across the regions implies that the distance from the Syrian border is the major factor in Syrian refugees’ destination choice. However, when we look at the secondary migration, by which I mean the destination after the initial entrance to the border regions, the distance from the border matters less. While some regions with lower distance received almost no refugees, regions that are much further such as Istanbul and Izmir received refugees up to 2% of their population. By directly looking at the distribution map, it can be argued that the factors such as the economic opportunity and ethnic enclave play a significant role in the endogenous selection of the secondary destination (Borjas, 2003; Card, 2009). Considering this fact, I estimate the primary migration impact (exogenous) and the secondary migration impact (endogenous) separately.

### 3. Primary migration analysis

This part of the study analyzes the labor market impacts of the refugee influx in the primary migration regions that consist of the three regions; TR13, TR24, and TR25 (Hatay, Gaziantep, and Sanliurfa), which are closer to the conflict area and received the highest number of refugees (8%–14%) relative to their native population.

#### 3.1. Estimation strategy

I employed a standard difference-in-differences approach in estimating the primary migration impact by forming a comparison group from the statistical regions that received an ignorable level of refugees relative to their population.

The construction of comparison group is the key factor in such a difference in differences setup because the validity of difference in differences estimation requires the comparison group (1) not to be affected from the treatment and (2) present parallel trends in terms of the outcome variables before and after the treatment. To satisfy these requirements; first, I formed a pool of potential control regions by excluding the regions refugee to native ratio of which exceeds 1%. Then, I ranked the potential control regions according to their correlations with the annual average of treatment regions in terms of the key outcome variables (labor force participation, employment, and wage) using the pre-treatment data (2005–2012). Taking the simple average of these rankings for each outcome variable, I chose three regions (TR5-Denizli, TR6-Manisa, and TR9-Ankara) that have the highest pre-existing correlation with the treatment regions as my control group.

Another important issue is the time of treatment. The AFAD (2013) survey provides significant information to determine the

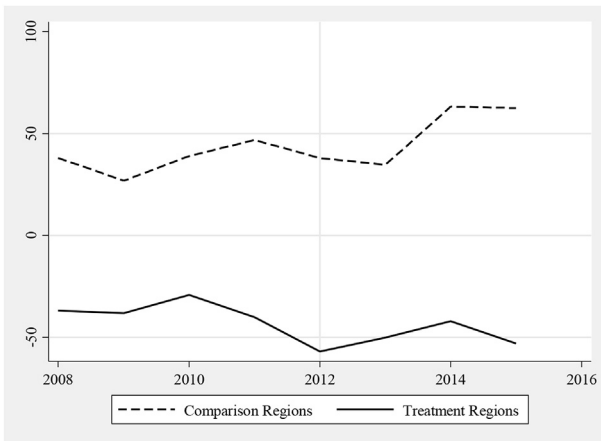


Fig. 3. Net within country migration by regions.

Source: Turkish Statistical Institute, Address Based Population Registration System.

Table 1  
Summary statistics.

Variable	Control Group		Treatment Group	
	2012	2015	2012	2015
<b>Males</b>				
Labor force participation rate	0.773	0.781	0.682	0.725
Unemployment rate	0.066	0.067	0.106	0.149
Monthly wages	1301	1768	946.9	1326
Age	37.38	37.81	33.96	34.56
High school graduation rate	0.404	0.432	0.256	0.282
Formal employment share	0.744	0.790	0.508	0.595
Manufacturing employment share	0.152	0.174	0.173	0.190
Small firm employment share	0.635	0.570	0.720	0.656
Observation #	21731	21338	14785	16870
<b>Females</b>				
Labor force participation rate	0.373	0.389	0.177	0.217
Unemployment rate	0.099	0.113	0.085	0.157
Monthly wages	1218	1553	881.5	1203
Age	37.47	37.89	34.03	34.49
High school graduation rate	0.315	0.350	0.147	0.189
Formal employment share	0.499	0.602	0.282	0.379
Manufacturing employment share	0.0938	0.118	0.0995	0.0790
Small firm employment share	0.686	0.623	0.797	0.703
Observation #	22994	22285	16131	17907

Note: Observations are weighted by the sampling weighting coefficients provided by the data source.

period in which we should have first seen the labor supply impacts of the Syrian refugees, which is the main concern of this study. The survey results imply that a very big majority of refugees were living in the refugee camps as of early 2013 and those refugees living outside of the camps at that time had much better preexisting income than the refugees in the camps (meaning a lesser necessity to work). Based on this fact, I selected 2012 as the pre-treatment period (in contrast to 2011 in former studies) and 2015 as the post-treatment year. Doing so, the aim is to disentangle the labor market impacts of Syrian Civil War on the border treatment regions (due to overall economic shock) from the refugees' labor supply impact. If there exists an impact on the overall economy in those treatment regions due to the conflict in Syria,<sup>1</sup> these effects should have been already seen in 2012 since the conflict started around the

<sup>1</sup> In September 2009 visa requirement was lifted mutually between the two countries. This policy change substantially increased the regional economic activity as can be noted from the differentially better employment levels in the region between 2009 and 2011 (Fig. 5).

mid of 2011. Selecting year 2012 as the base year also narrows the time between the pre-treatment and the post-treatment period. The longer the treatment period, the more likely to obtain biased estimates because there may be other policies affecting the treatment regions differentially independent of the refugee shock. Nevertheless, for the sake of comparability I carry out robustness checks for various treatment periods and control groups, as well.

One final concern in estimating the impact of such a large migration shock is the possibility of a downward bias in the treatment effects if immigrants are crowding out the natives from the treatment regions. I plotted the net internal migration pattern of natives over time on Fig. 3 to check whether the Syrian refugee influx led to the outmigration of the natives in the treatment regions. The treatment regions experience net outmigration historically; however, we do not observe a significant change in the trend during the treatment period. Furthermore, the level of outmigration declines slightly between 2012 and 2015. The Household Labor Force Survey data also confirms this result. The survey includes information on individuals' mobility across provinces and shows that the ratio of the individuals that moved into the treatment regions in a year is volatile overtime but there is no substantial change from 2011 to 2015 (only around 0.5%).

Based on the above discussion, below is the reduced form estimating equation for the probability of being employed (an OLS version of this equation is used for the wage estimation):

$$\text{Probit}(E_{ijt}) = \alpha_0 + X_{ijt}\beta + \alpha_1 \text{Treat}_j + \alpha_2 \text{Post}_t + \alpha_3 \text{Post}_t \times \text{Treat}_j + \varepsilon_{ijt} \quad (1)$$

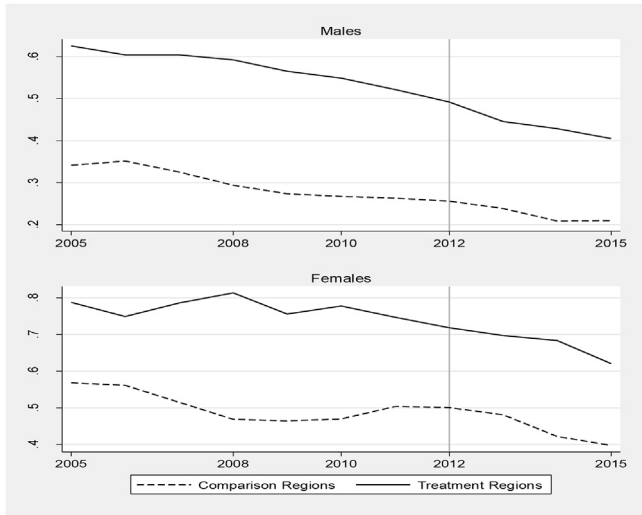
where;  $E_{ijt}$  is the indicator of being employed conditional on labor force participation for the individual  $i$  in region  $j$  at time  $t$ ,  $\text{Treat}_j$  is a dummy variable and equal to 1 if the individual is living in a treatment region,  $\text{Post}_t$  is a dummy variable and equal to 1 if the individual is surveyed in the post-treatment year,  $\text{Post}_t \times \text{Treat}_j$  is equal to 1 if the individual is living in a treatment region and surveyed after the treatment otherwise zero,  $\alpha_0$  is the constant term,  $X_{ijt}$  is a vector of explanatory variables including age, square of age, marital status, education dummies, region dummies, and the probability weight provided by the data source, and  $\varepsilon_{ijt}$  is the unobserved error term. The key coefficient in this equation is  $\alpha_3$  representing the impact of the refugee influx on the probability of employment for natives.

### 3.2. Data and summary statistics

Micro level annual Household Labor Force Survey data for the period from 2004 to 2016 is obtained from the Turkish Statistical Institute (TurkStat). These surveys are carried out annually with almost 400 thousand individuals and provide detailed information on both individual and work specific characteristics. The number of Registered Syrian immigrants at province level as of October 2015 is obtained confidentially from the Ministry of Interior. And finally the natives' internal migration data is obtained from TurkStat.

Table 1 presents the weighted mean values of some key variables across the regions before and after the treatment. The table provides a preliminary evidence for the impacts of Syrian Refugee Crisis on Turkey at the regional level. Labor force participation rate substantially increases in the treatment regions (by 4.3 percentage points for males and 4.0 percentage points for females) while the increase is much lower in the comparison regions. Such a big jump





**Fig. 4.** Informal employment trends across treatment and comparison regions. Source: TURKSTAT Household Labor Force Surveys 2005–2016. (Represents weighted average of the individuals between 15 and 65 y.o. only)

in the labor force participation rate might be result of the increase in living expenses in the region<sup>2</sup> or due to the added worker effect.<sup>3</sup>

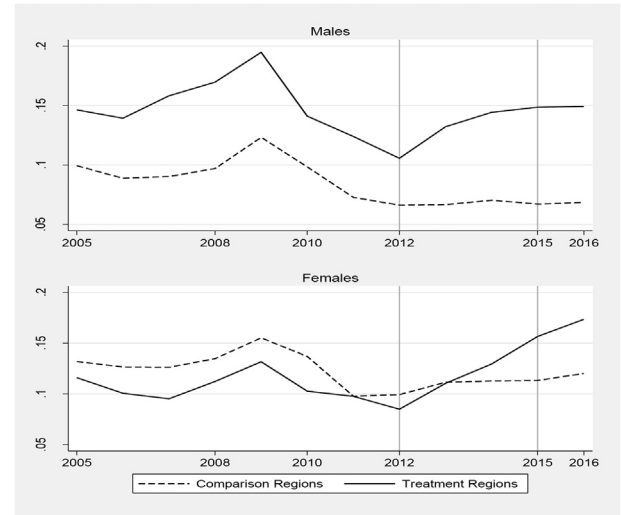
There is a differential change in the regional unemployment rates, as well. The male unemployment rate stays almost the same and the female employment declines by 1.4 percentage points in the comparison regions. However, the unemployment rate increases by 4.3 and 7.2 percentage points for males and females in the treatment region, respectively.

Informal employment share in total employment declines substantially in both treatment and comparison regions but the decline is higher especially for males in the treatment regions.<sup>4</sup> In Fig. 4, I compared the informal employment trends across the treatment and comparison regions overtime to check if this decline is due to a trend shift after the migration shock. Graphical illustration shows that the informal employment trend is negative in both regions historically. However, the decline in the informal employment is faster in the treatment regions (probably more responsive to the government policies targeting informal employment because of the significant baseline differences across the regions). The graph does not provide any visual evidence for a migration induced trend shift in the informal employment. Thus, what captured by Wagner and Del Carpio (2015) after the migration shock (the native employees' upgrading to formal jobs) is likely to be a result of the differences in the pre-treatment trends across the regions. Nevertheless, we may expect a

<sup>2</sup> According to the housing price index across provinces provided by the Central Bank of the Republic of Turkey, the housing prices increased around 50.1% in the treatment regions from 2011 to 2014 whereas the increase was about 32.5% in the control regions.

<sup>3</sup> The added worker effect suggests that labor supply of a household increases when a member of that household becomes unemployed. Labor force participation trends across gender and age groups represents no differential increase among females in the treatment regions relative to the control regions but that youth labor force participation rises significantly suggesting a possible added worker effect through children.

<sup>4</sup> An inter-ministerial strategic action plan was put into place for a more collaborative fight against the informal employment in Turkey in 2011. Since then, the informal employment across the country has significantly declined. We observe this dramatic change in the sample of this study as well. Overall formal employment rate rises for males (females) both in the treatment and comparison regions by 8.7 (9.7) and 4.6 (10.3) percentage points respectively. This historical trend shift needs to be taken into account while linking the impact of the refugee influx to the job upgrading of the natives over the treatment period.



**Fig. 5.** Unemployment by gender.

Source: TURKSTAT Household Labor Force Surveys 2005–2016. (Represents weighted average of the individuals that participate in the labor market and are between 15 and 65 y.o. only)

moderate increase in the formal employment because of the rise in the number of the public service workers that are classified as formal and skilled jobs. Another factor that may lead to increase in the formal employment is that the increase in the overall output disproportionately increases the skilled/unskilled jobs ratio due to the higher substitutability of the low-skilled labor with the immigrants.

There are also significant baseline differences in terms of skilled labor share, manufacturing employment share, and firm size between treatment and control regions. Considering baseline differences across the regions, making judgements simply based on the changes of the mean values may not represent the facts therefore we need to control for the individual characteristics to obtain a more reliable causal explanation.

I estimate the impact of the refugee influx on two outcome variables; employment and log real hourly wages (wage + bonus and other extra payments). The effect is estimated for each sub-groups of gender, skill, age, and industry to account for the heterogeneous impacts.

### 3.3. Employment results

Fig. 5 shows the average unemployment trends in the treatment and comparison regions across genders (see Figure A- 1 and Figure A- 2 in Appendix for the unemployment trends by education, age, and sector sub-groups). Overall, this graphical illustration confirms that the parallel trends assumption is largely satisfied before the treatment period and shows that there is a big trend shift in both male and female unemployment rate after 2012 in the treatment regions.

Table 2 represents the employment estimation results of equation (1) for both genders and their skill, experience and industry sub-samples. The first column is the probit estimates and the second is the calculated differential change in the probability of employment.<sup>5</sup> Estimates suggest a statistically significant (at the 1% level) and consistent negative treatment effect on both the male

<sup>5</sup> Differential change in the probability of employment in the treatment regions is calculated using the probability estimates provided with the margin command in the Stata (Williams, 2012).

**Table 2**  
Employment Probit estimation results in the primary migration.

Sample	MALES			FEMALES		
	N	(1) Probit Estimate (Standard Error)	(2) Differential change in the probability of employment	N	(3) Probit Estimate (Standard Error)	(4) Differential change in the probability of employment
All	54,426	−0.192*** (0.0335)	−0.034	22,929	−0.368*** (0.0557)	−0.042
<b>Education sub-groups</b>						
Elementary&less (<6 years)	22,378	−0.180*** (0.0523)	−0.032	10,636	−0.512*** (0.0989)	−0.017
Middle school (8 years)	11,665	−0.283*** (0.0671)	−0.059	2,698	−0.332** (0.142)	−0.047
High school (11 years)	10,925	−0.100 (0.0795)		3,545	−0.180 (0.123)	
College&above (>11 years)	9,458	−0.175* (0.100)	−0.018	6,050	−0.367*** (0.109)	−0.072
<b>Age sub-groups</b>						
15–25 y.o.	9,842	−0.247*** (0.0665)	−0.061	4,603	−0.472*** (0.102)	−0.093
26–40 y.o.	22,226	−0.174*** (0.0540)	−0.032	9,791	−0.330*** (0.0800)	−0.054
41–55 y.o.	17,894	−0.217*** (0.0626)	−0.031	6,976	−0.407*** (0.142)	−0.010
55–65 y.o.	4,464	0.156 (0.138)		1,559	−0.544 (0.473)	
<b>Industry sub-groups</b>						
Agriculture	9,407	−0.0306 (0.108)		7,706	−0.737*** (0.174)	−0.018
Manufacturing	10,572	−0.248*** (0.0777)	−0.036	2,446	−0.440** (0.181)	−0.076
Construction	6,134	−0.283*** (0.0797)	−0.085	227	−0.225 (0.688)	
Services	27,946	−0.211*** (0.0517)	−0.026	11,866	−0.200*** (0.0775)	−0.029

Note: Robust standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers individuals who are in the labor force and between the ages of 15 and 65. Control variables are age, age square, education dummies, marital status, region dummies.

and female employment, corresponding to a 3.4 and 4.2 percentage points declines in the probability of male and female employment conditional on being in labor force.

Sub-sample estimates show that the probability of male employment declined by around 3–6 percentage points for those with an education less than 11 years whereas the decline is not statistically significant among high school graduates and only significant at 10% level for college graduates with a lower magnitude (1.8 percentage points). The negative impact on skilled labor force seems to be contradictory to the theoretical expectations since the refugees are particularly substitute for unskilled native workers. However, in the case of Turkey the treatment regions experience an exogenous shock impacting the regional economy through two main channels; an increase in the labor supply and a possible contraction in the regional economy due to the conflict in the Syrian border. Hence, the negative but relatively smaller negative impact on the skilled native workers is likely to be driven by the overall economic impact of the conflict. Another possible explanation is the increase in the labor force participation of young educated family workers due to the added worker effect.

Disaggregation by age sub-groups implies a larger and more precise negative treatment effect on the younger individuals. The probability of employment declines by about 6.1 percentage points among the male individuals between 15 and 25 years old whereas the decline is around 3 percentage points for the 26–55 age groups and not statistically significant for the 55–65 age group. Combining these results

with the higher negative impact on the less-skilled individuals confirms the theoretical predictions regarding the vulnerability of the less-experienced and less-educated groups against the migration shock.

Finally, the disaggregation by industry sub-groups<sup>6</sup> shows a decline in the male employment in all four main sectors in the treatment regions relative to the comparison regions. However, the Probit estimates suggest that the negative treatment effect is statistically significant only for manufacturing, construction, and services sectors with 3.6, 8.5, and 2.6 percentage points declines in the probability of employment respectively. The impact is not statistically significant in the agricultural sector.<sup>7</sup>

Female employment by education sub-groups represents a similar pattern to the male employment. The treatment effect is negative and statistically significant at 1% level for those individuals with the lowest (elementary) and highest educational attainment (college) while the impact is not statistically significant for high school graduates. Excluding those individuals who were not in the job market in the previous year does not impact the sign of the coefficients as shown on the column (5). Estimation by the age sub-groups generates similar results to the males as well. Those females between 15 and 25 years old are the ones most affected from the treatment with a 9.3 percentage point decline in the probability of employment. Lastly, when classified by the industry, treatment effects are negative and statistically significant in all sectors except construction but larger in magnitude in the agriculture and manufacturing sectors.

I finally check the existence of occupational upgrading from

<sup>6</sup> The sector of individuals currently unemployed is proxied by previous work experience. Thus, the sample in this exercise is limited to those individuals with previous work experience since we have no sector information on first time job seekers.

<sup>7</sup> No impact on the males in the agricultural sector should not be surprising as majority (75% in 2012 in the treatment region) of them work as self-employed or family worker.

informal to formal employment in the treatment regions as suggested by Del Carpio and Wagner (2015). My results are in line with the findings of Del Carpio and Wagner such that the probability of formal employment for males increases by 2.6 percentage points in the treatment regions relative to the comparison regions. The occupational upgrading is heterogeneous across age groups and found to be significant for only elderly. The impact is not statistically significant for females. When combined with the overall employment estimation, these results suggest that Syrian refugee influx led to a decline in the employment probability of less educated and young natives while increasing the probability of formal employment for experienced male workers.

### 3.4. Wage estimation and results

Following is the estimating equation for the natural logarithm of the real hourly wage:

$$\ln(W_{ijt}) = \gamma_0 + Q_{ijt}\beta + \gamma_1 Treat_j + \gamma_2 Post_t + \gamma_3 Post_t \times Treat_j + \varepsilon_{ijt} \quad (2)$$

where  $W_{ijt}$  is the real hourly wage (wage + bonus and other payments) of an individual  $i$  working in the private sector<sup>8</sup> in region  $j$  at time  $t$ .<sup>9</sup>  $Treat_j$  is equal to 1 if the individual is living in a treatment region,  $Post_t$  is equal to 1 if the individual is surveyed in the post-treatment year,  $Post_t \times Treat_j$  is equal to 1 if the individual is living in a treatment region and surveyed after the treatment,  $Q_{ijt}$  is a vector of explanatory variables including age, square of age, marital status, education dummies, region dummies, work specific characteristics such as temporary job, part time, and informality status, firm specific characteristics such as industry type and firm size, and  $\varepsilon_{ijt}$  is the unobserved error term. The key coefficient in this equation is  $\gamma_3$  representing the impact of the refugee influx on the log real hourly wages of the natives.

Fig. 6 represents the historical trends of the weighted average of the hourly wages across regions by gender (see Appendix Figure A-3 and Figure A-4 for the sub-samples by education, age, industry, and firm size). Pre-existing parallel trends assumption is satisfied almost perfectly in both overall and sub-categorical trends. Graphically, it is difficult to observe a differential trend change in both male and female wages after the refugee shock. The mean wages increase in both regions; however, the magnitude of increase is relatively lower in the treatment regions. The picture becomes clearer when we look at the trends at more disaggregated level. Less-skilled and less-experienced individuals and those sectors composed of the more of the most vulnerable individuals seem to be relatively worsened after the refugee shock in the treatment region. Nevertheless, graphical evidence does not present a dramatic shift in the relative wage trends.

Table 3 represents the OLS estimates of the treatment effect for the males and females including all individuals and sub-groups separately. Male real wages in the treatment regions decline by almost 7.9% after the treatment. Estimation by the sub-groups shows that the treatment effect is heterogeneous across skill and age groups and industries.

The negative wage impact is around 10% for those who have eight years or less education and statistically significant at the 1% level while the impact is negative in sign but insignificant on the high

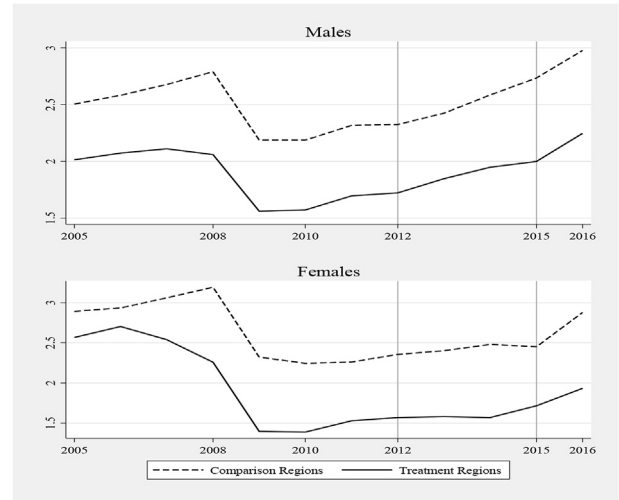


Fig. 6. Real Hourly Wages by gender. Source: TURKSTAT Household Labor Force Surveys 2005–2016. (Represents weighted average of the individuals between 15 and 65 y.o. only. Public workers are excluded)

school graduates and even positive on the college graduates but not statistically significant. Disaggregation by the age categories yields very different results as well. Those between 15 and 25 years old experience the highest wage decline with 14% and those between 26 and 40 years old also receive a wage decline around 6.5% because of the shock. Both estimates are statistically significant at the 1% level. The sign of the treatment effect is still negative but small in magnitude and not statistically significant for the older age groups.

Sampling by the four main sectors generates more heterogeneous results. The most dramatic impact seems to be on those working in the agricultural sector, who experienced a 29% wage decline as a result of the migration shock. The second and third most effected sectors were the construction and services with declines by 15.3% and 4.6% respectively. Those impacts are all statistically significant at the 1% level. The magnitude is lower and less precise for the manufacturing sector. Finally, sampling by the size of firm correlates with those results as well. Those employed in the firms with less than 10 workers had about 14.2% decline in their wages while there was no statistically significant impact on those employed in the larger firms. These findings are not much surprising as the individuals with lower skills and experience and those working in more informal sectors are expected to be the most vulnerable in response to such a big labor supply shock.

Female wage estimates are not much different from the male estimation in terms of the most affected groups; however, the magnitude of the negative impact is substantially larger for certain groups. The overall impact on the female wages is negative but statistically insignificant at the 10% level. Those with less than 6 years of education experience 13.1% decline in their wages while the impact is not statistically significant on those with middle school and high school education. Moreover, the college graduates receive 15.7% increase on their wages and this impact is statistically significant at the 10% level. The wages of the younger females (15–40 yo) decline around 8% while the rest has no statistically significant change in their wages. In accordance with these results, female workers in the agricultural sector experience the most dramatic decline in their wages with almost 41% loss as the lower skilled informal workers dominate this sector. The treatment effect is negative in the manufacturing and construction sectors as well. However, the impact is positive but not statistically significant in the services sector, which represents the 2/3 of all females in the sample. Finally, when the female workers are grouped by the size of the firm they

<sup>8</sup> Since public workers' wages are determined by the central government at national level, public sector workers are excluded from the sample.

<sup>9</sup> Real hourly wage is calculated by the following formula:  $W_{ijt} = ((\text{earnings} \times 12) / (52 \times \text{weekly work hours})) \times (100 / \text{regional price index}_t)$ .



**Table 3**  
Wage estimation in the primary migration.

	MALES				FEMALES			
	N	(1) All	(2) Formal	(3) Informal	N	(4) All	(5) Formal	(6) Informal
All	23,321	-0.0789*** (0.0113)	-0.017 (0.013)	-0.200*** (0.027)	6985	-0.00407 (0.0269)	0.105*** (0.030)	-0.144*** (0.052)
<b>Education sub-groups</b>								
Elementary&less (<6 years)	8981	-0.102*** (0.0166)	-0.036** (0.018)	-0.191*** (0.038)	2402	-0.127*** (0.0428)	0.066 (0.044)	-0.186*** (0.064)
Middle school (8 years)	5930	-0.120*** (0.0209)	-0.054** (0.023)	-0.226*** (0.044)	987	-0.0640 (0.0589)	-0.018 (0.071)	-0.060 (0.107)
High school (11 years)	5596	-0.0360 (0.0227)	0.001 (0.024)	-0.227*** (0.077)	1846	0.0552 (0.0405)	0.072* (0.044)	0.022 (0.126)
College & above (>11 years)	2814	0.0423 (0.0457)	0.060 (0.048)	0.017 (0.155)	1750	0.157** (0.0661)	0.192*** (0.070)	-0.604** (0.283)
<b>Age sub-groups</b>								
15-25 y.o.	5152	-0.141*** (0.0223)	-0.041 (0.025)	-0.266*** (0.044)	1854	-0.0771* (0.0434)	0.122** (0.050)	-0.323*** (0.079)
26-40 y.o.	11,510	-0.0648*** (0.0157)	-0.017 (0.017)	-0.187*** (0.050)	3420	0.0796** (0.0383)	0.098** (0.042)	-0.025 (0.099)
41-55 y.o.	5982	-0.0449* (0.0243)	0.028 (0.027)	-0.216*** (0.053)	1597	-0.0879 (0.0624)	-0.001 (0.082)	-0.117 (0.093)
55-65 y.o.	677	-0.0362 (0.0850)	-0.010 (0.116)	-0.057 (0.122)	114	0.0501 (0.214)	0.416 (0.315)	-0.004 (0.300)
<b>Industry sub-groups</b>								
Agriculture	940	-0.290*** (0.0610)	-0.137 (0.138)	-0.315*** (0.076)	559	-0.410*** (0.0945)	NR	-0.406*** (0.098)
Manufacturing	7723	-0.0410** (0.0180)	-0.014 (0.019)	-0.157*** (0.057)	1523	0.117** (0.0506)	0.118** (0.056)	0.118 (0.127)
Construction	3201	-0.153*** (0.0316)	-0.045 (0.037)	-0.299*** (0.062)	160	0.308** (0.146)	0.467*** (0.157)	NR
Services	11,457	-0.0457*** (0.0169)	-0.009 (0.019)	-0.126*** (0.038)	4743	0.0341 (0.0312)	0.091** (0.036)	-0.063 (0.067)
<b>Firm size sub-groups</b>								
Small (<10 employee)	10,021	-0.142*** (0.0175)	-0.033 (0.022)	-0.219*** (0.030)	2898	-0.0708 (0.0438)	0.105* (0.058)	-0.109* (0.062)
Medium (11–50)	6581	-0.0264 (0.0205)	0.002 (0.022)	-0.141** (0.066)	2107	-0.00142 (0.0427)	0.089* (0.052)	-0.345*** (0.105)
Large (>50)	6719	0.0122 (0.0202)	0.012 (0.021)	0.035 (0.114)	1980	0.139*** (0.0467)	0.133*** (0.048)	0.093 (0.220)

Note: Robust standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers the individuals who are in the labor force and between the ages of 15 and 65. Public workers, whose wages are determined at national level, and the workers who are paid too low or too high are excluded from the sample. The control variables are age, age square, tenure, tenure square, marital status, education dummies, full time, temporary job, social security, economic activity, and region dummies. NR (Not reported due to low sample size).

work in, the impact is negative but statistically insignificant in the firms with less than 50 workers. The coefficient turns out to be positive and highly significant in the larger size firms (14%).

### 3.5. Heterogeneous treatment effect on the informal employees' wages

Regression analysis by the sub-groups of individuals suggests that the higher the ratio of informal employment in a sample the larger the level of negative wage effect in that sample. Column 2 and 3 (column 5 and 6 for females) of Table 3 represent the comparison of the overall estimates to a further difference-in-differences specification for the informal employees (not registered to the social security system) by regressing the same specification on formal and informal employees separately.

Indeed, both male and female wage results show that a very big portion of the negative wage effects are arising from the decline in the informal workers' wages suggesting that the informality plays a larger role among the youth and those working in the small firms.

### 3.6. Robustness and Placebo Tests

The comparison group in the baseline specification is constructed in a way that it follows a very similar pre-existing trend to the treatment group. The aim was to reduce the probability that the differential change in both the employment and wage outcomes in

the treatment regions are because of the pre-existing differential trends between the treatment and comparison regions. However, the differential change in the outcomes may be arising from some other sources that are affecting the certain parts of the country including the treatment region. Moreover, it is likely to have some other random shocks happening in the selected comparison regions during the treatment period.

To address such concerns, a larger set of comparison group that is including all regions that received negligible number of refugees is formed as a robustness check. Further, some placebo tests are carried out by arbitrarily forming treatment regions from the west, middle, and east of the country. Appendix Table A- 1 and Table A- 2 show the comparison of these tests to the baseline results for the male and female employment respectively. Similarly, appendix Table A- 3 and Table A- 4b represent the comparisons for the wage estimation. In each table, column (1) shows the results of the preferred specification from the baseline estimations, column (2) represents the results when 2011 is chosen as the pre-treatment year, column (3) represents the results when all immigrant-free regions are included as the comparison regions, and finally columns (4) through (6) provide the results of the placebo tests.

Comparing the results in column (1) through (3), the results in both the employment and wage estimation are in the same direction and close to each other in terms of the signs and magnitudes. Analysis of the placebo tests shows that the treatment effect becomes insignificant and takes the opposite sign to the baseline estimations in

**Table 4**  
Male employment Probit estimation results in the secondary migration.

Sample	MALES				FEMALES			
	N	(1) Probit	(2) IVProbit-Distance	(3) IVProbit-Ethnic E.	N	(4) Probit	(5) IVProbit-Distance	(6) IVProbit-Ethnic E.
All	224,572	-0.0116 (0.0123)	0.00788 (0.00944)	1.87e-05 (0.0123)	106,656	-0.0120 (0.0144)	0.0105 (0.00957)	0.000685 (0.0108)
<b>Education sub-groups</b>								
Elementary& less (<6 years)	87,665	-0.00233 (0.0117)	0.0134 (0.0101)	0.00537 (0.0132)	51,487	-5.68e-05 (0.0176)	0.0202* (0.0110)	0.0131 (0.0145)
Middle school (8 years)	224,572	-0.0207** (0.00940)	-0.00624 (0.00952)	-0.0155 (0.0111)	13,389	0.00116 (0.0147)	0.0246** (0.0110)	0.00998 (0.0141)
High school (11 years)	50,311	-0.0114 (0.0202)	0.0169 (0.0145)	0.00730 (0.0186)	16,929	-0.0265 (0.0162)	-0.00310 (0.0111)	-0.0266 (0.0183)
College&above (>11 years)	39,560	-0.0238 (0.0184)	0.0101 (0.0105)	0.000834 (0.0100)	24,851	-0.0180 (0.0156)	0.00653 (0.0132)	0.00914 (0.00906)

Note: Clustered (year, region) standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers individuals who are in the labor force and between the ages of 15 and 65. Additional control variables are age, age square and marital status, time, region, and education dummies.

most of the cases. Moreover, those regions in the eastern part of the country (column 6) that are sharing the common labor market characteristics with the baseline treatment regions represent a completely opposite outcome. These placebo tests confirm that the treatment regions did not experience differential employment and wage effects randomly but because of the migration effect.

#### 4. Secondary migration analysis

The refugees' possibility of returning to the home country has declined over time because of the increasing level of tension in the Syrian conflict. This fact has turned the refugee migration phenomena from being a temporary and regional issue to a one permanent and national level in Turkey. The official registration data has shown that the Syrian refugee population has spread across all the cities in the country as of 2015 October. But of course, the allocation of Syrian refugees across the cities is not homogenous. Some parts of the country have received more refugees relative to the other regions depending on the distance from the conflict area and the region level factors such as the economic conditions and cultural similarity to the origin region. A specific estimation strategy is constructed to estimate the labor market impacts of Syrian refugee shock in these secondary migration regions, which do not have border to the conflict area in Syria.

##### 4.1. Estimation strategy

The biggest concern for the area approach in estimating the labor market impact of immigration is the endogeneity associated with immigrants' selection of destination region. If immigrants are choosing to reside in those regions with better economic conditions, a standard OLS estimation is likely to produce downward biased negative impacts on the labor market outcomes. To handle this problem, I employed an instrumental variable strategy following David Card's (2009) ethnic enclave approach.

There is no information on the ethnicity of Turkish citizens at regional level therefore we are not able know how many Arabs or other ethnicities live in a region. However, the address based population data contains information on the original province of ancestries of an individual. I postulate that the Turkish natives living in the primary migration regions must be the best proxy for the cultural and behavioral tendencies of Syrian refugees in Turkey since the natives living in those regions share the most common ethnic, geographical, and historical characteristics with the Syrians.<sup>10</sup> In other words, the Syrian refugees in Turkey are very

likely to follow the pre-existing within country migration pattern of the natives living in the primary migration regions. Using the pre-treatment 2011 Address Based Population Registration data, I calculated a ratio representing the density of individuals originally from the primary regions among native immigrants for each region. This ratio is constructed as the instrumental variable for the migration density (MR) of Syrian refugees across the 26 statistical regions in Turkey. It takes into account not only the geographical distance factor but also the cultural and ethnic factors affecting the migration destination decision. This IV should not carry information on the economic trends in the destination regions because it measures the ratio of the native immigrants from the primary regions relative to the native immigrant population not to the total regional population. The IV can be formulated as follows:

$$NMR_j = \frac{Primary_j}{\sum_{k=1, k \neq j}^n R_{jk}} \quad (3)$$

where  $NMR_j$  is the ratio of the native immigrants from the primary regions to the total native migrants in region  $j$  in 2011,  $Primary_j$  is the total number of the native immigrants from the primary migration regions in the region  $j$  in 2011, and  $R_{jk}$  is the number of native immigrants from region  $k$  in the region  $j$  in 2011. The correlation between MR and NMR is highly positive (0.72) suggesting a powerful relationship between the instrument and the instrumented variable.

##### 4.2. Employment estimation

Below is the estimating equation for the impact of the migration shock on the employment level in the secondary migration destinations.

$$\text{Probit}(E_{ijt}) = \rho_0 + X_{ijt}\beta + \rho_1 \text{Post}_t + \rho_2 \text{Post}_t \times MR_j + \varepsilon_{ijt} \quad (4)$$

where  $E_{ijt}$  is the indicator of being employed conditional on being in the labor force for the individual  $i$  in region  $j$  at time  $t$ ,  $\text{Post}_t$  is equal to 1 if the individual is surveyed in post-treatment year,  $MR_j$  is the ratio of the number of Syrian refugees registered in region  $j$  to the native population in that region in 2015,  $X_{ijt}$  is a vector of explanatory variables including age, age square, marital status, education dummies, and  $\varepsilon_{ijt}$  is the unobserved error term. The key coefficient in this equation is  $\rho_2$  representing the impact of the refugee influx on the probability of employment for natives. Differently from the standard difference-in-differences estimation, the treatment is assumed to be affecting all the regions but at a varying degree. The aim of instrumenting MR with NMR is to identify an unbiased estimate for the employment effect. The

<sup>10</sup> Both regions were part of the Ottoman Empire until the early 20th century.

**Table 5**  
Log hourly wage estimation results in the secondary migration.

Sample	MALES			FEMALES				
	N	(1) Probit	(2) IVProbit-Distance	(3) IVProbit-Ethnic E.	N	(4) Probit	(5) IVProbit-Distance	(6) IVProbit-Ethnic E.
All	97,697	-0.0109** (0.00472)	-0.00462 (0.00317)	-0.0142** (0.00637)	32,434	-0.00901** (0.00367)	-0.00378 (0.00236)	-0.00842** (0.00424)
<b>Education sub-groups</b>								
Elementary& less (<6 years)	34,603	-0.00854* (0.00425)	-0.00590* (0.00302)	-0.0141*** (0.00429)	10,371	-0.00915 (0.00800)	0.00613 (0.00404)	0.000970 (0.00565)
Middle school (8 years)	23,824	-0.0152** (0.00612)	-0.00529 (0.00460)	-0.0201** (0.00886)	5089	-0.0266*** (0.00714)	-0.0164*** (0.00497)	-0.0212*** (0.00546)
High school (11 years)	26,240	-0.0131** (0.00605)	-0.00761 (0.00582)	-0.0125* (0.00722)	8614	-0.0233*** (0.00644)	-0.0207*** (0.00488)	-0.0275*** (0.00755)
College&above (>11 years)	13,030	-0.0132 (0.00854)	0.000722 (0.00543)	-0.0113 (0.00963)	8360	0.00655 (0.00579)	-0.000746 (0.00542)	-0.00369 (0.00436)
<b>Age sub-groups</b>								
15-25 y.o.	21,004	-0.0166** (0.00665)	-0.00583 (0.00632)	-0.0216*** (0.00764)	8669	-0.0178*** (0.00321)	-0.0132*** (0.00266)	-0.0194*** (0.00432)
26-40 y.o.	48,547	-0.00762* (0.00444)	-0.00306 (0.00370)	-0.0108* (0.00633)	15,974	-0.00787*** (0.00271)	-0.00514* (0.00307)	-0.00844*** (0.00297)
41-55 y.o.	25,126	-0.0133** (0.00504)	-0.00598** (0.00285)	-0.0129** (0.00561)	7283	-0.00890 (0.0104)	0.00308 (0.00769)	-0.00215 (0.00928)
55-65 y.o.	3020	-0.00195 (0.00582)	-0.00244 (0.00507)	-0.0153* (0.00791)	508	0.0429*** (0.0153)	0.0572*** (0.0161)	0.0335* (0.0176)
<b>Industry sub-groups</b>								
Agriculture	2692	0.00852* (0.00494)	0.0130** (0.00551)	0.00165 (0.00584)	1236	-0.00644 (0.0159)	0.0121 (0.00953)	0.00660 (0.00941)
Manufacturing	33,361	-0.0240*** (0.00767)	-0.0178** (0.00726)	-0.0233** (0.00907)	9183	-0.0201*** (0.00692)	-0.0164** (0.00710)	-0.0162*** (0.00627)
Construction	12,729	0.00278 (0.00542)	0.0174** (0.00814)	0.00687 (0.00474)	575	0.0720*** (0.0106)	0.0665*** (0.0101)	0.0610*** (0.0123)
Services	48,915	-0.0115** (0.00473)	-0.00728** (0.00315)	-0.0186*** (0.00634)	21,440	-0.00838*** (0.00173)	-0.00779*** (0.00145)	-0.0121*** (0.00286)
<b>Firm size sub-groups</b>								
Small (<10 employee)	39,476	-0.0129** (0.00483)	-0.00596 (0.00440)	-0.0171*** (0.00526)	12,167	-0.00970* (0.00575)	-0.000630 (0.00313)	-0.00514 (0.00455)
Medium (11–50)	27,487	-0.0157** (0.00689)	-0.00707 (0.00516)	-0.0155* (0.00912)	9709	-0.0182*** (0.00676)	-0.00846 (0.00538)	-0.0112* (0.00666)
Large (>50)	30,734	-0.00688** (0.00328)	-0.00372 (0.00277)	-0.0117* (0.00643)	10,558	-0.0104** (0.00490)	-0.00759 (0.00676)	-0.0205*** (0.00619)

Note: Clustered (year, region) standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers the individuals who are in the labor force and between the ages of 15 and 65. Public workers, whose wages are determined at national level, and the workers who are paid too low or too high are excluded from the sample. Control variables are age, age square, tenure, tenure square, marital status, education dummies, region dummies, full time, temporary job, social security, economic activity.

estimates from a specification in which the geographical distance from the conflict area is used as an IV are also provided among the results as a comparison to the IV in [Del Carpio and Wagner \(2015\)](#).

[Table 4](#) represent the Probit and ivProbit results from the regressions for the overall male and female employment and by sub-education groups for each gender. First column represent the Probit estimates with no instruments, the second column represents the results from an ivProbit estimate when the treatment variable is instrumented with the geographical distance from the conflict area, and the third column shows the ivProbit estimates from the proposed ethnic enclave IV in this study, which is the pre-existing within country migration pattern of the natives from the primary migration region. The standard errors are clustered by region and year.

The coefficient on the treatment variable is negative in some cases for both males and females when all skill groups are included in the regressions. However, those effects are not statistically significant. Running the regressions for sub-samples of education does not generate a consistent negative or positive impact on the skilled or unskilled native employees. Based on these estimates, we cannot conclude a negative causal relationship between the refugee influx and natives' employment in the secondary migration regions as we did so in the primary migration regions.

#### 4.3. Wage estimation

The wage outcomes are estimated with a similar OLS and IV version of equation (4) by adding the work specific controls. The

impact of the refugee influx on the real hourly wages of the natives is illustrated on [Table 5](#).

The coefficient on the treatment variable for the entire male sample is negative and statistically significant in the baseline and preferred IV specifications. According to the preferred specification in column (3), a one percent refugee influx to the regional population leads to 1.4% decline in the overall male wages. Running the regression for the sub-samples of education, age, industry, and firm size generates significant heterogeneous negative impacts on the most vulnerable groups as it was the case for the primary migration region. The results of the preferred specification implies that a one-unit increase in the refugees to regional population ratio decreases the real hourly wages of the natives with less than 6 years of education and between 6 and 8 years of education by 1.4% and 2.0% respectively. The impact is lower on the high school graduates with a lower precision. There exists no statistically significant impact on the college graduates. Comparing the baseline OLS specifications to the preferred IV specification, the size of the treatment coefficient gets larger in magnitude and becomes more precise for low-skilled groups with the ethnic enclave IV. This result explains the downward bias concerns for the OLS estimation. On the other hand, geographical distance IV in columns 3 and 4, which is included to be a comparison for [Carpio and Wagner \(2015\)](#)'s suggestion, produces results that are lower in magnitude relative to the OLS.

When the individuals are categorized by their age group, the negative impact becomes lower in magnitude as the age increases. The youngest group with ages between 15 and 25 years old

experiences 2.1% decline in their wages in response to a unit increase in the migration ratio. Combining this result with the previous education sub-group estimations it can be argued that the less-skilled and lower educated male individuals are the most affected group from the refugee influx among the male in the secondary migration areas. Further analysis of the male wages with the sector groups shows that the only negative and statistically significant impact is on those working in the services and manufacturing sectors with 1.9% and 2.2% declines, respectively. Finally, those working in the small firms with less than 10 workers are the mainly affected group with 1.7% decline in overall wages.

The female wages for the entire sample generates a statistically significant migration impact as well with a magnitude of 0.8%. The age and sector sub-samples results conforms with the male results suggesting a statistically significant impact on the youth with ages 15–25 years old and on those in the services and manufacturing sectors. However; in contrast to the male wages, there exists a statistically significant impact on the higher skilled female workers while the impact on the low-skilled females is statistically insignificant. Similarly, those working in the larger firms seem to be negatively impacted whereas the impact is not statistically significant on those working in the small firms. This kind of contradictory results hardly make economic sense as they conflict with the theoretical predictions of a low-skilled labor intensive migration shock. On the other hand, this may be a sign of the replacement of the native female workers with the male native workers. The upgrading of native male workers from small firms to larger firms and more skilled jobs may lead to more competition in these categories across genders.

#### 4.4. Robustness checks

Table A- 5 and Table A- 6 represent the results of the various robustness exercises for males and females respectively. Column (1) represents the results from the baseline ethnic enclave IV estimation, column (2) represents the results from the baseline specification when the informal workers are excluded from the sample, column (3) shows the results when 2011 is chosen as the pre-treatment year, and finally column (4) illustrates the falsification test results when the baseline estimation is carried out with the false treatment period (2009–2011) to see if there exists a pre-occupying trend on those groups that are being negatively affected from the migration shock.

As oppose to the primary migration results, excluding informal workers from the sample does not affect the treatment coefficient. Even the magnitude and the significance gets larger. The differential outcomes across the primary and secondary migrations may be arising due to the differential size of the informal sectors in those regions.

Changing the pre-treatment year to 2011 as in the column (3) does not affect the results significantly for both males and females. Falsification test in the column (4) generates completely different results to the baseline estimation suggesting no pre-existing trend for those groups that are affected from the refugee influx.

## 5. Conclusion

This paper investigates the causal relationship between the Syrian refugee induced increase in labor supply and natives' labor market outcomes in Turkey using the micro level Household Labor Force Surveys. Migration impact is analyzed in two distinct categories considering the motives behind the migration decision. The initial migration to the border regions is assumed to be completely exogenous and defined as the primary migration. Thus, a standard difference in differences strategy is employed to estimate the labor market impacts in those regions. On the other hand, migration from the

primary regions towards the inner regions in Turkey (secondary migration) has suffered from the endogenous selection issues. To handle these concerns, I developed an instrumental variables estimation method for the secondary migration impact following David Card (2009)'s ethnic enclave approach.

The analysis of primary migration effect suggests that both the male and female employment are being negatively impacted with declines in the probability of employment by 3.4 and 4.2 percentage points, respectively, conditional on labor force participation. The negative employment impact is much larger among the less-educated males with less than 11 years of schooling (around 5 percentage points), not statistically significant for the high school graduates, and statistically significant at 10 percent level for college graduates (1.8 percentage points). The impact is negative and statistically significant across all age groups that are younger than 55 years old and larger in magnitude among the youth. Female employment results are largely in parallel with the male results. Wage impact is negative across both genders as well; however, the negative impact is clearer on the least educated and less experienced individuals and in the sectors that are more prone to the informal employment. Males with less than 5 years and 5–8 years of education experienced a wage decline of about 10.2% and 12% respectively whereas the impact on those with higher education is statistically insignificant. Females with less than 5 years of education, accounting for 36% of the female workers, had a wage decline of 12.7% with no statistically significant negative impact on those with higher education as well. Disaggregation by age, sector, and firm size show that the negative wage impact is larger on the less experienced individuals, the sectors with larger informal employment, and the small firms. A further disaggregation by the informality status shows that the decline in the wages of informal workers is indeed the main contributor of the negative wage effects.

Secondary migration estimation generates no statistically significant employment effect on both genders but negative wage effects primarily on males. The negative wage effects are more prominent on the natives that are more likely to be substituted by the informal employment of the refugees. Accordingly, a one-unit increase in the refugees to regional population ratio reduces the wages of males with an education less than five years and 5–8 years by 1.4% and 2.0% respectively. The negative impact is statistically significant for those between ages 15–25 (2%), working in the services sector (1.9%), and working in small firms (1.7%). The female wage estimates are not in line with the male results and requires a further analysis for the possible causes.

Findings in this study confirm the wage predictions of classical models such that an unskilled intensive migration shock reduces the wages of unskilled native workers. Contradicting employment results between the primary migration analysis (strongly negative) and the secondary migration analysis (no impact) are also in line with the theory suggesting that migration may result in unemployment among natives in case of an inelastic capital in an economy. The capital stock was probably elastic enough to adjust the additional labor supply due to relatively lower levels of refugee to regional population ratio in the secondary migration regions and vice versa in the primary migration regions.

## Conflicts of interest

The author declares that he has no conflict of interest.

## Acknowledgement

I thank Devashish Mitra, Mary E. Lovely, Alfonso Flores-Lagunes, and seminar participants at Syracuse University and Central Bank of The Republic of Turkey. I would also like to thank the anonymous referees for insightful guidance.

APPENDIX

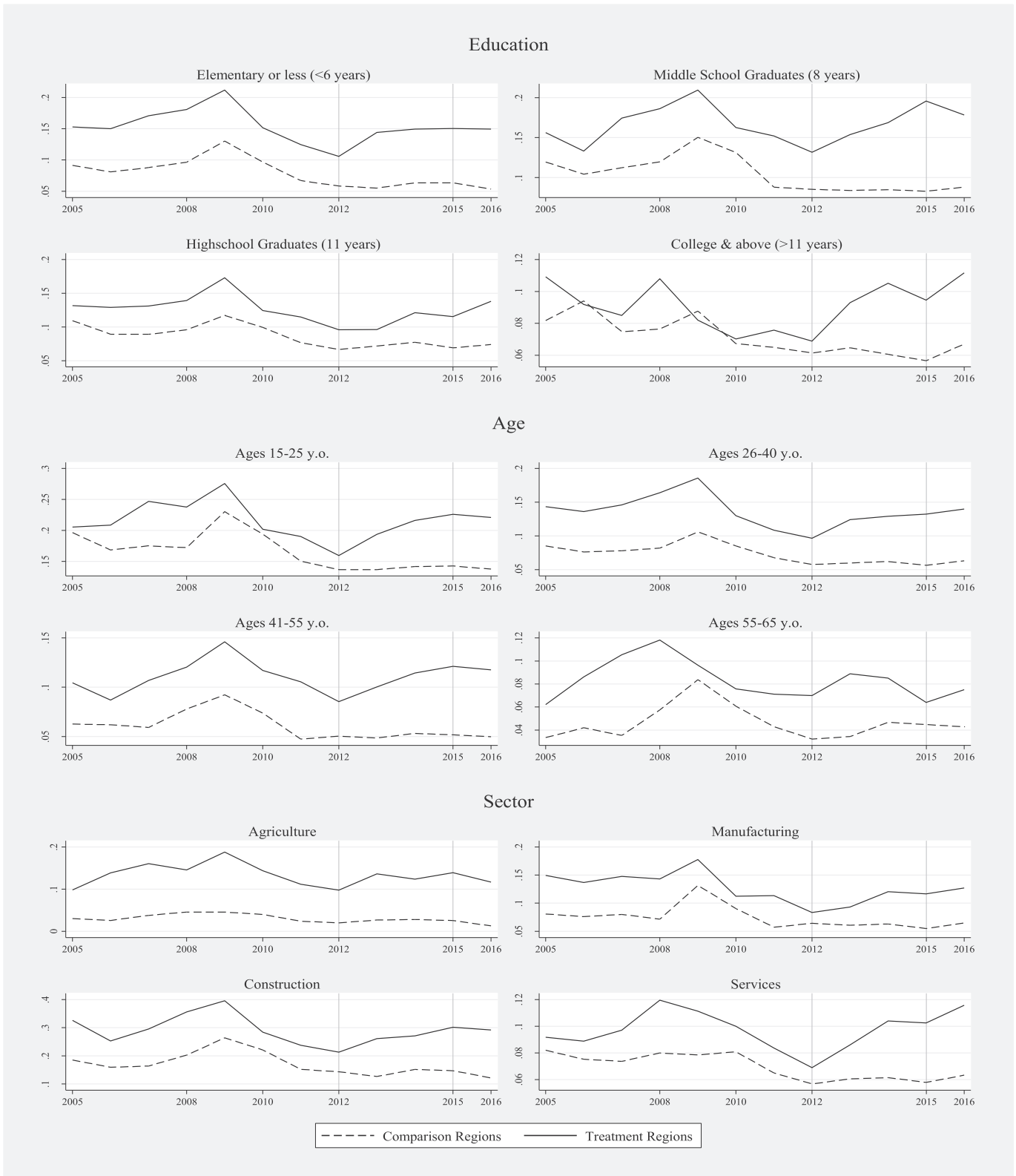
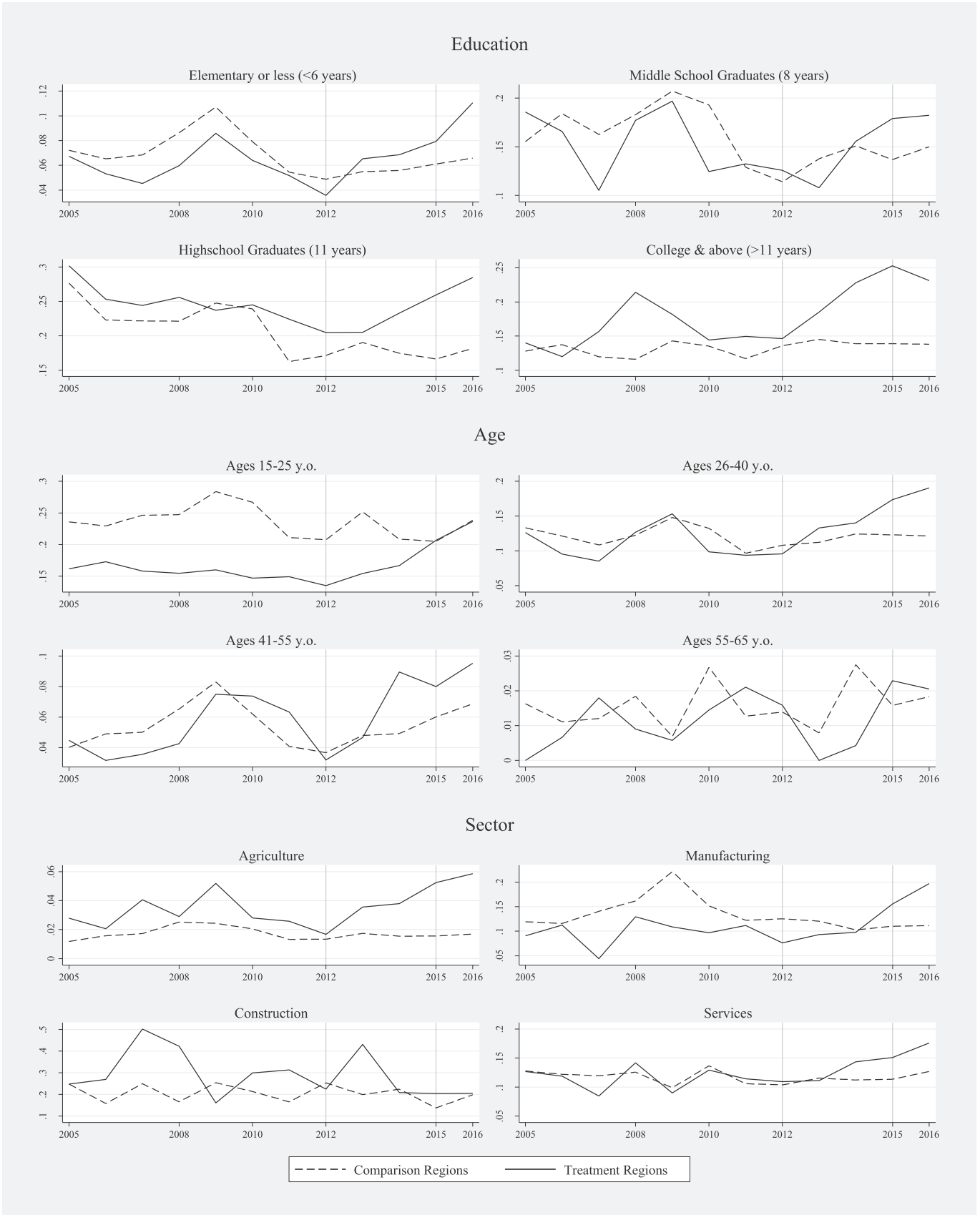


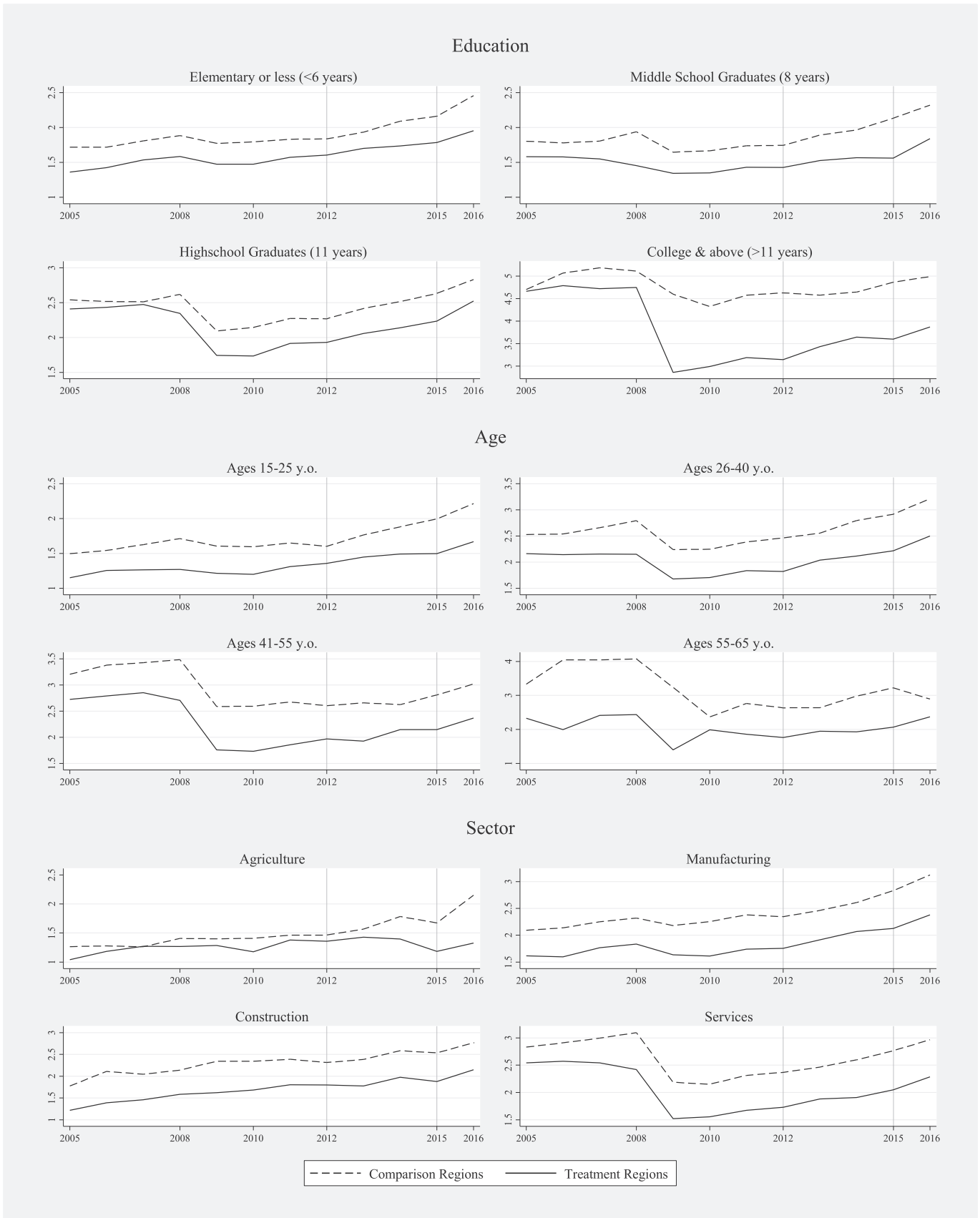
Fig. A1. Male Employment by Sub-groups.  
 Source: TURKSTAT Household Labor Force Surveys 2005–2016. (Represents weighted average of the individuals that participate in the labor market and are between 15 and 65 y.o. only)



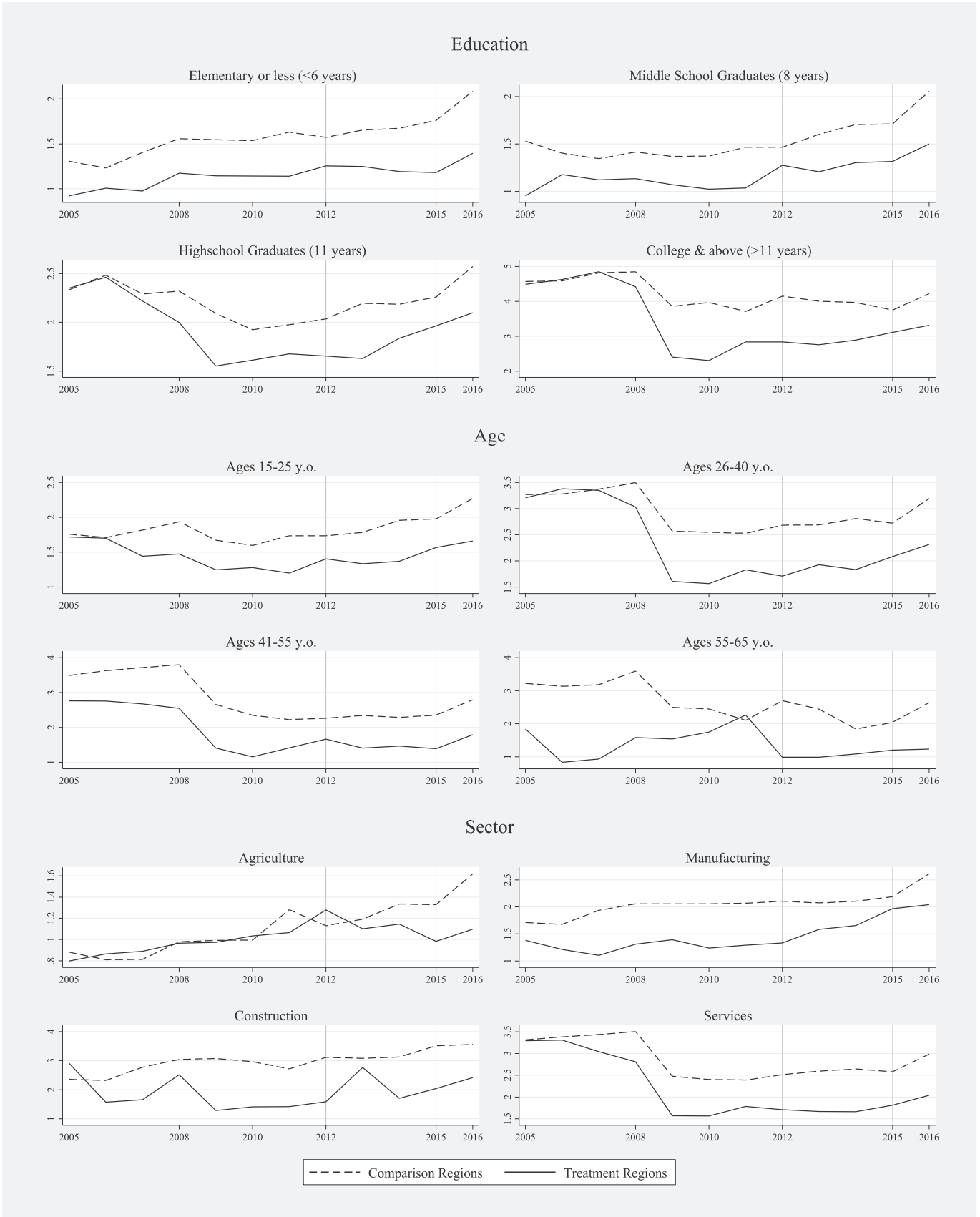


**Fig. A2.** Female Employment by Sub-groups.

Source: TURKSTAT Household Labor Force Surveys 2005–2016. (Represents weighted average of the individuals that participate in the labor market and are between 15 and 65 y.o. only)



**Fig. A3.** Male Wages by Sub-groups.  
 Source: TURKSTAT Household Labor Force Surveys 2005–2016. (Represents weighted average of the individuals between 15 and 65 y.o. only. Public workers are excluded)



**Fig. A4.** Female Wages by Sub-groups.  
 Source: TURKSTAT Household Labor Force Surveys 2005–2016. (Represents weighted average of the individuals between 15 and 65 y.o. only. Public workers are excluded)

**Table A1**  
Male Employment in the Primary Migration – Robustness and Placebo Tests

Sample	Probit Coefficients on treatment*post					
	(1) Baseline	(2) Baseline-2011	(3) Baseline-ALL	(4) Placebo-West	(5) Placebo-Mid	(6) Placebo-East
All males	-0.192*** (0.0335)	-0.140*** (0.0326)	-0.205*** (0.0272)	0.0193 (0.0351)	-0.0405 (0.0403)	0.249*** (0.0378)
<b>Education sub-groups</b>						
Elementary&less (<6 years)	-0.180*** (0.0523)	-0.146*** (0.0510)	-0.188*** (0.0399)	0.0131 (0.0589)	-0.0528 (0.0663)	0.189*** (0.0607)
Middle school (8 years)	-0.283*** (0.0671)	-0.187*** (0.0654)	-0.287*** (0.0537)	0.0497 (0.0732)	-0.125 (0.0813)	0.239*** (0.0766)
High school (11 years)	-0.100 (0.0795)	-0.0536 (0.0749)	-0.161** (0.0678)	0.0473 (0.0721)	0.108 (0.0847)	0.400*** (0.0815)
College & above (>11 years)	-0.175* (0.100)	-0.118 (0.102)	-0.171** (0.0870)	-0.0792 (0.0869)	-0.0493 (0.105)	0.243** (0.102)
<b>Age sub-groups</b>						
15-25 y.o.	-0.247*** (0.0665)	-0.187*** (0.0642)	-0.297*** (0.0524)	0.0514 (0.0721)	-0.0343 (0.0810)	0.343*** (0.0748)
26-40 y.o.	-0.174*** (0.0540)	-0.170*** (0.0521)	-0.176*** (0.0441)	-0.00179 (0.0579)	-0.0785 (0.0661)	0.232*** (0.0595)
41-55 y.o.	-0.217*** (0.0626)	-0.0683 (0.0614)	-0.224*** (0.0507)	0.0182 (0.0631)	0.0237 (0.0742)	0.123* (0.0729)
55-65 y.o.	0.156 (0.138)	0.0187 (0.137)	0.157 (0.112)	0.103 (0.129)	-0.0320 (0.154)	0.453** (0.181)
<b>Industry sub-groups</b>						
Agriculture	-0.0306 (0.108)	-0.0718 (0.105)	-0.181** (0.0708)	0.221* (0.132)	0.0626 (0.131)	0.476*** (0.125)
Manufacturing	-0.248*** (0.0777)	-0.0231 (0.0761)	-0.205*** (0.0637)	-0.0499 (0.0744)	-0.143 (0.0967)	0.238** (0.112)
Construction	-0.283*** (0.0797)	-0.221*** (0.0795)	-0.331*** (0.0621)	0.0578 (0.0936)	-0.0598 (0.103)	0.391*** (0.0853)
Services	-0.211*** (0.0517)	-0.158*** (0.0496)	-0.205*** (0.0437)	-0.0182 (0.0514)	0.0207 (0.0592)	0.0852 (0.0575)

Note: Robust standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers individuals who are in the labor force and between the ages of 15 and 65. Control variables are age, age square, education dummies, marital status, and region dummies.

**Table A2**  
Female Employment in the Primary Migration - Robustness and Placebo Tests

Sample	Probit Coefficients on treatment*post					
	(1) Baseline	(2) Baseline-2011	(3) Baseline-ALL	(4) Placebo-West	(5) Placebo-Mid	(6) Placebo-East
All females	-0.368*** (0.0557)	-0.263*** (0.0544)	-0.365*** (0.0498)	0.0682 (0.0433)	-0.187*** (0.0502)	0.0598 (0.0555)
<b>Education sub-groups</b>						
Elementary or less (<6 years)	-0.512*** (0.0989)	-0.373*** (0.0918)	-0.460*** (0.0873)	-0.0270 (0.0765)	-0.203** (0.0843)	0.000951 (0.106)
Middle school (8 years)	-0.332** (0.142)	-0.329** (0.144)	-0.298** (0.125)	0.120 (0.115)	-0.248* (0.137)	-0.0897 (0.155)
High school (11 years)	-0.180 (0.123)	-0.104 (0.117)	-0.231** (0.113)	0.222** (0.0900)	-0.0318 (0.109)	0.166 (0.119)
College & above (>11 years)	-0.367*** (0.109)	-0.316*** (0.114)	-0.350*** (0.0993)	-0.0917 (0.0842)	-0.250** (0.105)	0.0883 (0.109)
<b>Age sub-groups</b>						
15-25 y.o.	-0.472*** (0.102)	-0.360*** (0.0963)	-0.391*** (0.0884)	-0.0819 (0.0845)	-0.179* (0.0968)	-0.0113 (0.102)
26-40 y.o.	-0.330*** (0.0800)	-0.279*** (0.0817)	-0.349*** (0.0718)	0.0807 (0.0628)	-0.188** (0.0737)	0.0452 (0.0823)
41-55 y.o.	-0.407*** (0.142)	-0.0943 (0.124)	-0.434*** (0.129)	0.193** (0.0916)	-0.135 (0.108)	0.167 (0.131)
55-65 y.o.	-0.544 (0.473)	-0.328 (0.431)	-0.227 (0.417)	-0.119 (0.317)	-0.898** (0.427)	-0.574 (0.451)
<b>Industry sub-groups</b>						
Agriculture	-0.737*** (0.174)	-0.528*** (0.158)	-0.590*** (0.139)	-0.322** (0.162)	-0.282 (0.175)	0.213 (0.183)
Manufacturing	-0.440** (0.181)	-0.232 (0.172)	-0.441*** (0.163)	0.0327 (0.104)	-0.470*** (0.158)	0.524** (0.235)
Construction	-0.225 (0.688)	0.458 (0.495)	-0.462 (0.640)	-0.453 (0.374)	-0.331 (0.532)	0.424 (0.576)
Services	-0.200*** (0.0775)	-0.187** (0.0771)	-0.206*** (0.0708)	0.108* (0.0598)	-0.153** (0.0724)	0.00188 (0.0828)

Note: Robust standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers individuals who are in the labor force and between the ages of 15 and 65. Control variables are age, age square, education dummies, marital status, and region dummies.

**Table A3**  
Male Wages in the Primary Migration - Robustness and Placebo Tests

Sample	Coefficients on treatment*post					
	(1) Baseline	(2) Baseline-2011	(3) Baseline-ALL	(4) Placebo-West	(5) Placebo-Mid	(6) Placebo-East
All males	-0.0789*** (0.0113)	-0.0764*** (0.0114)	-0.0533*** (0.00969)	-0.0166 (0.0103)	-0.022 (0.013)	0.00712 (0.0137)
<b>Education sub-groups</b>						
Elementary&less (<6 years)	-0.102*** (0.0166)	-0.0991*** (0.0165)	-0.0714*** (0.0143)	-0.0192 (0.0156)	-0.044** (0.022)	-0.0207 (0.0209)
Middle school (8 years)	-0.120*** (0.0209)	-0.122*** (0.0210)	-0.0854*** (0.0180)	-0.0128 (0.0196)	-0.008 (0.024)	0.0309 (0.0259)
High school (11 years)	-0.0360 (0.0227)	-0.0293 (0.0222)	-0.000165 (0.0201)	-0.0634*** (0.0178)	-0.008 (0.024)	-0.00931 (0.0249)
College&above (>11 years)	0.0423 (0.0457)	0.0614 (0.0477)	0.0364 (0.0411)	0.0611* (0.0361)	-0.079 (0.050)	0.0923** (0.0465)
<b>Age sub-groups</b>						
15-25 y.o.	-0.141*** (0.0223)	-0.110*** (0.0224)	-0.0914*** (0.0182)	-0.0301 (0.0218)	0.002 (0.027)	0.0265 (0.0278)
26-40 y.o.	-0.0648*** (0.0157)	-0.0719*** (0.0156)	-0.0372*** (0.0135)	-0.0215 (0.0142)	-0.038*** (0.018)	-0.00659 (0.0188)
41-55 y.o.	-0.0449* (0.0243)	-0.0417* (0.0240)	-0.0362* (0.0216)	0.00109 (0.0203)	-0.027 (0.029)	-0.00618 (0.0275)
55-65 y.o.	-0.0362 (0.0850)	-0.157 (0.0968)	0.00657 (0.0749)	-0.0323 (0.0741)	-0.087 (0.107)	0.0427 (0.0994)
<b>Industry sub-groups</b>						
Agriculture	-0.290*** (0.0610)	-0.337*** (0.0630)	-0.263*** (0.0462)	-0.0842 (0.0688)	0.179** (0.083)	0.0656 (0.0864)
Manufacturing	-0.0410** (0.0180)	-0.0212 (0.0186)	-0.0121 (0.0152)	-0.0415*** (0.0157)	-0.010 (0.024)	0.0155 (0.0284)
Construction	-0.153*** (0.0316)	-0.133*** (0.0313)	-0.106*** (0.0248)	0.00439 (0.0347)	-0.023 (0.038)	-0.0257 (0.0336)
Services	-0.0457*** (0.0169)	-0.0521*** (0.0165)	-0.0309** (0.0148)	0.00318 (0.0155)	-0.035** (0.017)	0.0302* (0.0175)
<b>Firm size sub-groups</b>						
Small (<10 employee)	-0.142*** (0.0175)	-0.119*** (0.0174)	-0.102*** (0.0147)	-0.0231 (0.0175)	-0.045** (0.020)	-0.0104 (0.0198)
Medium (11–50)	-0.0264 (0.0205)	-0.0224 (0.0209)	-0.0196 (0.0180)	0.0189 (0.0200)	-0.002 (0.022)	0.0379 (0.0235)
Large (>50)	0.0122 (0.0202)	-0.00816 (0.0199)	0.0273 (0.0175)	-0.00924 (0.0161)	-0.007 (0.025)	0.00583 (0.0295)

Note: Robust standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1, The sample covers the individuals who are in the labor force and between the ages of 15 and 65. Public workers, whose wages are determined at national level, and the workers who are paid too low or too high are excluded from the sample. The control variables are age, age square, tenure, tenure square, marital status, education dummies, full time, temporary job, social security, economic activity, and region dummies.

**Table A4**  
Female Wages in the Primary Migration - Robustness and Placebo Tests

Sample	Coefficients on treatment*post					
	(1) Baseline	(2) Baseline-2011	(3) Baseline-ALL	(4) Placebo-West	(5) Placebo- Mid	(6) Placebo-East
All females	-0.00407 (0.0269)	0.0388 (0.0260)	-0.0116 (0.0254)	0.00720 (0.0166)	0.019 (0.023)	0.0679*** (0.0237)
<b>Education sub-groups</b>						
Elementary&less (<6 years)	-0.127*** (0.0428)	-0.0121 (0.0391)	-0.112*** (0.0405)	-0.0332 (0.0259)	-0.001 (0.035)	0.0377 (0.0455)
Middle school (8 years)	-0.0640 (0.0589)	0.0458 (0.0634)	-0.0679 (0.0563)	-0.0411 (0.0377)	-0.000 (0.052)	0.0520 (0.0540)
High school (11 years)	0.0552 (0.0405)	0.0717 (0.0448)	0.0413 (0.0380)	0.00851 (0.0265)	0.018 (0.039)	0.0715* (0.0376)
College&above (>11 years)	0.157** (0.0661)	0.0672 (0.0616)	0.125** (0.0633)	0.0391 (0.0414)	0.059 (0.064)	0.0827* (0.0485)
<b>Age sub-groups</b>						
15-25 y.o.	-0.0771* (0.0434)	0.0321 (0.0406)	-0.0572 (0.0404)	-0.0290 (0.0299)	0.004 (0.041)	0.0262 (0.0396)
26-40 y.o.	0.0796** (0.0383)	0.0610 (0.0383)	0.0470 (0.0361)	0.0407* (0.0239)	0.027 (0.033)	0.136*** (0.0332)
41-55 y.o.	-0.0879 (0.0624)	-0.0429 (0.0663)	-0.0811 (0.0579)	-0.0315 (0.0354)	0.003 (0.047)	-0.0365 (0.0602)
55-65 y.o.	0.0501 (0.214)	-0.580** (0.248)	0.141 (0.177)	-0.0931 (0.182)	0.159 (0.213)	-0.00471 (0.210)

(continued on next page)



Table A4 (continued)

Sample	Coefficients on treatment*post					
	(1) Baseline	(2) Baseline-2011	(3) Baseline-ALL	(4) Placebo-West	(5) Placebo- Mid	(6) Placebo-East
<b>Industry sub-groups</b>						
Agriculture	−0.410*** (0.0945)	−0.165** (0.0711)	−0.380*** (0.0820)	0.0205 (0.0984)	−0.067 (0.124)	1.255*** (0.216)
Manufacturing	0.117** (0.0506)	0.176*** (0.0586)	0.108** (0.0477)	−0.0103 (0.0266)	0.086** (0.039)	0.158*** (0.0526)
Construction	0.308** (0.146)	0.0462 (0.137)	0.325*** (0.113)	0.0371 (0.143)	0.127 (0.215)	0.465** (0.214)
Services	0.0341 (0.0312)	0.0567* (0.0327)	0.0282 (0.0291)	0.0178 (0.0223)	−0.002 (0.028)	0.0411 (0.0266)
<b>Firm size sub-groups</b>						
Small (<10 employee)	−0.0708 (0.0438)	0.0442 (0.0402)	−0.0754* (0.0407)	−0.0244 (0.0302)	0.016 (0.037)	0.0518 (0.0392)
Medium (11–50)	−0.00142 (0.0427)	0.0576 (0.0416)	0.00643 (0.0411)	0.0308 (0.0300)	−0.052 (0.039)	0.0931** (0.0362)
Large (>50)	0.139*** (0.0467)	−0.0216 (0.0566)	0.113** (0.0450)	0.0427 (0.0260)	0.087** (0.038)	0.0749 (0.0483)

Note: Robust standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers the individuals who are in the labor force and between the ages of 15 and 65. Public workers, whose wages are determined at national level, and the workers who are paid too low or too high are excluded from the sample. The control variables are age, age square, tenure, tenure square, marital status, education dummies, full time, temporary job, social security, economic activity, and region dummies.

Table A5

Male Wages in the Secondary Migration - Robustness and Falsification Tests

Sample	Coefficients on the treatment*post variable			
	(1) Baseline 2012–2015	(2) Formal 2012–2015	(3) 2011–2015	(4) 2009–2011
All males	−0.0142** (0.00637)	−0.0153** (0.00726)	−0.0121** (0.00609)	0.00913*** (0.00254)
<b>Education sub-groups</b>				
Elementary or less (<6 years)	−0.0141*** (0.00429)	−0.0159*** (0.00440)	−0.00835* (0.00433)	0.00850** (0.00351)
Middle school (8 years)	−0.0201** (0.00886)	−0.0197* (0.0111)	−0.0106 (0.00991)	0.00831** (0.00354)
High school (11 years)	−0.0125* (0.00722)	−0.0167** (0.00767)	−0.0209*** (0.00703)	0.00923*** (0.00221)
College & above (>11 years)	−0.0113 (0.00963)	−0.00964 (0.00920)	−0.0109 (0.00680)	0.00966 (0.00600)
<b>Age sub-groups</b>				
15–25 y.o.	−0.0216*** (0.00764)	−0.0222** (0.00878)	−0.0183** (0.00786)	0.0160*** (0.00470)
26–40 y.o.	−0.0108* (0.00633)	−0.0138* (0.00717)	−0.00938 (0.00668)	0.00466** (0.00221)
41–55 y.o.	−0.0129** (0.00561)	−0.0137** (0.00553)	−0.0110** (0.00434)	0.00981*** (0.00227)
55–65 y.o.	−0.0153* (0.00791)	0.00509 (0.0121)	5.36e-06 (0.00804)	0.0116 (0.00851)
<b>Industry sub-groups</b>				
Agriculture	0.00165 (0.00584)	0.00578 (0.00931)	0.0145*** (0.00489)	0.0157*** (0.00468)
Manufacturing	−0.0233** (0.00907)	−0.0259*** (0.00897)	−0.0218*** (0.00838)	0.00528*** (0.00199)
Construction	0.00687 (0.00474)	−0.000140 (0.00506)	0.00818 (0.00498)	0.00735 (0.00469)
Services	−0.0186*** (0.00634)	−0.0144** (0.00715)	−0.0187*** (0.00627)	0.0139*** (0.00224)
<b>Firm size sub-groups</b>				
Small (<10 employee)	−0.0171*** (0.00526)	−0.0190*** (0.00622)	−0.0138** (0.00637)	0.0136*** (0.00303)
Medium (11–50)	−0.0155* (0.00912)	−0.0151* (0.00884)	−0.00984 (0.00902)	0.00434 (0.00307)
Large (>50)	−0.0117* (0.00643)	−0.0127* (0.00719)	−0.0157*** (0.00424)	0.0113*** (0.00303)

Note: Clustered (year, region) standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers the individuals who are in the labor force and between the ages of 15 and 65. Public workers, whose wages are determined at national level, and the workers who are paid too low or too high are excluded from the sample. Control variables are age, age square, tenure, tenure square, marital status, education dummies, region dummies, full time, temporary job, social security, economic activity.

**Table A6**  
Female Wages in the Secondary Migration - Robustness and Falsification Tests

Sample	Coefficients on the treatment*post variable			
	(1) Baseline 2012–2015	(2) Formal 2012–2015	(3) 2011–2015	(4) 2009–2011
All females	–0.00842** (0.00424)	–0.0127*** (0.00429)	–0.0108 (0.00688)	0.00356 (0.00297)
<b>Education sub-groups</b>				
Elementary or less (<6 years)	0.000970 (0.00565)	–0.00899 (0.00644)	–0.00413 (0.00813)	0.00288 (0.00444)
Middle school (8 years)	–0.0212*** (0.00546)	–0.0183** (0.00845)	–0.00925 (0.00821)	–0.00209 (0.00745)
High school (11 years)	–0.0275*** (0.00755)	–0.0270*** (0.00936)	–0.0282** (0.0113)	0.0107** (0.00509)
College & above (>11 years)	–0.00369 (0.00436)	–0.00402 (0.00498)	–0.00704 (0.00492)	–0.000430 (0.00582)
<b>Age sub-groups</b>				
15–25 y.o.	–0.0194*** (0.00432)	–0.00956*** (0.00368)	–0.0213*** (0.00524)	0.0117** (0.00522)
26–40 y.o.	–0.00844*** (0.00297)	–0.0115*** (0.00383)	–0.00986 (0.00745)	0.00362 (0.00440)
41–55 y.o.	–0.00215 (0.00928)	–0.0367*** (0.0114)	–0.00396 (0.0116)	–0.0104** (0.00434)
55–65 y.o.	0.0335* (0.0176)	0.0724* (0.0391)	–0.0203 (0.0124)	0.0490*** (0.0167)
<b>Industry sub-groups</b>				
Agriculture	0.00660 (0.00941)	–0.0422 (0.0569)	0.0227*** (0.00777)	–0.00318 (0.00755)
Manufacturing	–0.0162*** (0.00627)	–0.0218*** (0.00782)	–0.0255*** (0.00870)	–0.00439 (0.00633)
Construction	0.0610*** (0.0123)	0.0786*** (0.0134)	0.0712*** (0.0210)	–0.0167 (0.0286)
Services	–0.0121*** (0.00286)	–0.0145*** (0.00318)	–0.0147*** (0.00549)	0.00529* (0.00316)
<b>Firm size sub-groups</b>				
Small (<10 employee)	–0.00514 (0.00455)	–0.0107 (0.00793)	–0.0106 (0.00804)	0.00219 (0.00305)
Medium (11–50)	–0.0112* (0.00666)	–0.0123** (0.00543)	–0.00450 (0.00841)	0.0125*** (0.00347)
Large (>50)	–0.0205*** (0.00619)	–0.0200*** (0.00641)	–0.0202*** (0.00684)	–0.0102* (0.00577)

Note: Clustered (year, region) standard errors in parentheses \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The sample covers the individuals who are in the labor force and between the ages of 15 and 65. Public workers, whose wages are determined at national level, and the workers who are paid too low or too high are excluded from the sample. Control variables are age, age square, tenure, tenure square, marital status, education dummies, region dummies, full time, temporary job, social security, economic activity.

## References

- Akgündüz, Yusuf Emre, van den Berg, Marcel, Hassink, Wolter, 2015. The Impact of Refugee Crises on Host Labor Markets: the Case of the Syrian Refugee Crisis in Turkey. IZA Discussion Paper No, p. 8841.
- BBC Middle East, "Timeline: How the Syrian Conflict has Spread" <<http://www.bbc.com/news/world-middle-east-28850956>> (12/05/2014).
- Borjas, George J., 2003. The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market. Q. J. Econ. 118 (4), 1335–1374.
- Card, David, 2001. Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. J. Labor Econ. 19 (1), 22–64.
- Card, David, Richard, T. Ely, 2009. Lecture: "immigration and inequality". Am. Econ. Rev.: Papers & Proceedings 99 (2), 1–21.
- Ceritoglu, Evren, Burcu Gürcihan, Yüncüler, Huzeyfe, Torun, Tumen, Semih, 2015. The Impact of Syrian Refugees on Natives' Labor Market Outcomes in Turkey: Evidence from a Quasi-experimental Design. IZA Discussion Paper No, p. 9348.
- Del Carpio, Ximena V., Wagner, Mathis C., 2015. The Impact of Syrians Refugees on the Turkish Labor Market. Policy Research Working Paper; No. WPS 7402. World Bank Group, Washington, D.C.
- Dustmann, Christian, Frattini, Tommaso, Preston, Ian P., 2013. The effect of immigration along the distribution of wages. Rev. Econ. Stud. 80 (1), 145–173.
- Dustmann, Christian, Uta, Schönberg, Jan, Stuhler, 2017. Labor supply shocks, native wages, and the adjustment of local employment. Q. J. Econ. 132 (1), 435–483.
- Glitz, Albrecht, 2012. The labor market impact of immigration: a quasi-experiment exploiting immigrant location rules in Germany. J. Labor Econ. 30 (1), 175–213.
- Lewis, Ethan, 2012. Immigration and Production Technology. NBER Working Paper No. 18310.
- Ottaviano, Gianmarco, Peri, Giovanni, 2012. Rethinking the effect of immigration on wages. J. Eur. Econ. Assoc. 10 (1), 152–197.
- AFAD, 2013. Republic of Turkey Prime Ministry Disaster and Emergency Management Presidency, Syrian Refugees in Turkey, 2013 Field Survey Results.
- UNOCHA, "Syrian Crises Situation Overview", Retrieved from <<http://syria.unocha.org/>>, (1/15/2016).
- Williams, Richard, 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. STATA J. 12 (2), 308–331.