# Is It Merely A Labor Supply Shock?

# Impacts of Syrian Migrants on Local Economies in Turkey

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**Abstract**

We use a large and geographically varying inflow of over 2.5 million Syrian migrants to Turkey between 2012 and 2015 to study the effect of migration on local economies. We do not find adverse employment or wage effects for native-born Turkish workers overall, or for those without a high school degree. These results are robust to a range of strategies to construct reliable control groups. To rationalize the findings, we document the importance of three migration-induced demand channels: the complementarity between native and migrant labor, housing demand, and increased entrepreneurial activities.

Keywords: Syrian Immigration, Labor Market, Construction Industry, Firm Formation, Generalized Synthetic Control

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## Introduction

As of 2019, more than 6 million Syrians have left their country since the Syrian Civil War began in 2011. Such a large displacement of people has affected many countries around the world. As a result, the immigration of refugees has taken center stage in political debates. The traditional economic model tends to paint a relatively pessimistic picture for affected natives about effects of immigration. It predicts a wage, and possibly employment, decline (Borjas, 2013; Dustmann et al., 2016). On the other hand, migrant labor may complement native labor and increase the productivity (Ottaviano and Peri 2012). In addition, along with their labor power, migrants bring their purchasing power, increase the demand in the host regions (Constant 2014; Peri 2014). Depending on the relative intensities of the labor supply and labor demand boosts, the potential adverse effects for affected natives might not materialize even in the short run. Therefore, the overall effect on native workforce is theoretically ambiguous. The empirical evidence on the labor market impacts is mixed, and the debate continues (Borjas and Monras, 2016; Card, 2009; Clemens and Hunt, 2017; Peri, 2012, 2014, 2016).

We add to this literature by empirically examining labor demand as well as labor supply effects of the unusually large, sudden, and geographically concentrated migration flow of more than 2.5 million Syrians into Turkey between 2012 and 2015 using a novel and robust approach. We analyze how the affected native workers' wages and employment prospects change by the arrival of the Syrian migrants to Turkey. We do not find adverse employment or wage effects for native-born Turkish workers. Then, to rationalize the results, we assess presence of migration-induced demand channels.

The overwhelming majority of the Syrian migrants do not have a high school degree and they are not Turkophones. Thus, if the migration shock affects only labor supply, then the natives with less than high school education (LTHS) in the host regions would be adversely affected. Using the

TURKSTAT Household Labor Force Survey (HLFS) from 2004 to 2015, we initially document how employment levels and wages of Turkish workers of different skill levels change as a result of the Syrian migration.

Then, we turn to the migration-induced demand channels to explain the former results. The demand channels might enable local economies to fully or partly absorb the labor supply shock. We examine three of them: (i) the native-migrant complementarity, (ii) housing demand, and (iii) increased entrepreneurial activities of Syrians and non-Syrians in the host regions. To individually assess their existence, we show changes in the affected natives' job characteristics, in the number of residential building permits, and in the new business creation by Syrians and non-Syrians. Thus, our article is the first to explore different demand channels in providing a comprehensive picture about the effects of the Syrian migration on Turkish workers and local economies in Turkey.

One main empirical challenge in estimating effects of migration is that migrants may prefer to go to regions that are experiencing an economic boom, so underlying pre-existing economic trends and regional business cycles might severely bias the estimates. Although the current case is a forced migration and most Syrians reside in the border regions due to their proximity to Syria, not due to their growth performances, there is no guarantee that the host regions and others have, on average, similar business cycles. To address the potential endogeneity due to the unobserved differences in the host regions and the rest of the country, we employ the Generalized Synthetic Control (GSC) method proposed by Xu (2017) in addition to more traditional least squares (OLS) and two-stage least squares (2SLS) estimators. The GSC builds a data-driven factor-based regression model similar to the interactive fixed effects model in Bai (2009), (not the synthetic control model along the lines of Abadie et al. (2010)) and purges time-varying unobserved factors, such as industry trends, that violate the identifying assumption in an event study design. Furthermore, it allows to delineate dynamic effects of the shock on the outcome variables, thus provides a highly transparent picture about the time paths of effects. This exercise reveals whether the impact changes over time. More importantly, it shows if the parallel trends assumption is violated during the pre-treatment period—an indicator that the causal interpretation is unwarranted. Therefore, our use of the GSC, in addition to the traditional model specifications, provides causally interpretable results.

## Background

### Open door but particularities

The Syrians fleeing from the war initially migrated to three bordering countries: Lebanon, Jordan and Turkey.[1] Turkey, as the northern neighbor of Syria, has followed a relatively open-door policy since the beginning of the Syrian Civil War in 2011. This resulted in more than 2.5 million Syrians to enter Turkey in a short time, between 2012-2015 (see figure 1). Although this number corresponds to 3% of the overall Turkish population, the residential distribution of the migrants is highly non-uniform. The majority of the Syrian migrants reside in the border regions, due to their geographical proximity to Syria (see figure 2). The government-built Temporary Accommodation Camps are also close to the border, though they provide accommodation to only a small share of the migrants, suggesting that the actual number of Syrians migrants is considerably larger than the anticipated one.[2]

Legally, Syrians fleeing from the civil war are considered as "guests", not refugees (Özden, 2013). This prevents them from seeking asylum in another country and they cannot formally work. As a

[1] For a detailed investigation of Syrian migrants' labor market effects in Jordan, please see Fallah et al. (2019).
[2] In fact, only in 2014, the Turkish government started distributing identity cards. The cards enabled the migrants to have access to certain services including aid, healthcare, and education outside the camps. The cards improved the quality of the data about the migrants.

result, only a negligible share of migrants has work permits. However, they can and do work informally.[3]

## Syrian Forced Migrants in Turkey

The overwhelming majority of the Syrian migrants are non-Turkophones (in Jordan and Lebanon native population speak Arabic) and more than 90% of them do not have a high school degree. Table 1 presents a descriptive summary of the demographic characteristics of the (15+) Syrian migrants in Turkey. For comparative purposes, we also present comparable statistics for all (15-64) the natives, and for the (15-64) natives that reside in the regions where the ratio of migrant population to the natives is greater than 10%. The table shows that the migrants have less education than both native samples. While 92.4% of them have no high school degree, this number is 66.1% for all natives, and 76.6% for the latter sample. They are also younger and less likely to be woman than natives.

Due to the migration, the working age population of the border regions with less than high school (LTHS) education has increased by approximately 15% between 2011 and 2015. As a result of this, one expects that the potential adverse effects of the migration on the native workforce is most visibly appears for the lower-skilled LTHS workers in the border regions.

## Literature Review on the Syrian Forced Migration in Turkey

The Syrian refugee crisis led to a substantial number of studies investigating the impact on natives' labor market outcomes (employment and wages) in the host countries, and on the local economies

[3] By January 2016, only 7,351 of them had work permits. However, there are approximately 400,000 Syrian nationals that are informally employed by the end of 2015 (Üstun 2016).

(local trade balance, prices, school class sizes, firm entry). The most common methods in these studies are traditional difference-in-differences or two-stage least squares estimators given the unexpected nature of refugee flow to Turkey. Below, we initially review the studies concerning labor markets and then discuss those on local economies.

**Effects on Natives' Employment and Wages**

Currently, the debate on the impact of the Syrian migration to Turkey mostly revolves around its effects on employment. The findings from empirical studies on the subject are mixed. Six of the studies that are closely related to ours are Akgündüz et al. (2015), Aksu et al. (2018), Del Carpio and Wagner (2015), Tümen (2016)[4], Bağır (2017), and Altındağ et al. (2018). The former two studies argue that there is no net significant employment effect on native workers; while the latter four claim a significant decline in employment for native workers that are similarly skilled as the Syrian migrants.

Akgündüz et al. (2015) and Tümen (2016) employ difference-in-differences models and compare the post-treatment period (2012 and onwards) with the previous years. While the regions that are considered as treated are highly similar in both of the studies, the main difference lies in the way they construct the control regions. Akgündüz et al. prefer a less restrictive approach and includes every non-treated region in the control group in their baseline specification. They find no employment effects for lower or higher skilled workers, some decline in in-migration but no change in out-migration from the treated regions. Tümen, on the other hand, includes only the regions that are geographically close to the treated regions, and concludes that the Syrian migration increased unemployment, particularly among lower skilled native workers.

[4] An expanded version of Tumen (2016) is published as Ceritoglu et al. (2017).

Del Carpio and Wagner (2015), Bağır (2017), and Altındağ et al. (2018) employ two-stage least squares models.[5] Del Carpio and Wagner compare years 2011 and 2014, and find negative employment effects of the Syrian migrants on lower-skilled natives. Both Bağır (2017) and Altındağ et al. (2018) agrees with this conclusion, with the latter study using data sets ranging from 2004 to 2016. In addition, both studies find that the migration wave decreased native LTHS wages.[6]

Finally, Aksu et al. (2018) uses both the least squares and the two-stage least squares approaches and relax the common trend assumption implicit in the previous studies by including time trends, or region-by-year fixed effects.[7] They find large and negative employment effects for men in informal sector. However, the large and negative employment effects are balanced by large increases in formal employment.

**Effects on Local Economies**

Two of the earlier studies on the Syrian migrants' impact on local economies are Öztürkler and Göksel (2015) and Bahçekapılı and Çetin (2015). Both are descriptive and suggestive in nature. They are published before the government started to release reliable regional distribution of the Syrian forced migrants in Turkey. For the year 2013, Öztürkler and Göksel (2015) report improvements in trade balances, and increases in home sales in the treated provinces. They also find that the local inflation rises due to the migration. Bahçekapılı and Çetin (2015) agrees that the regional trade balances have improved.

[5] An earlier version of the current paper is cited by Altindag et al. (2018).
[6] We should note that the wage variable constructed by Altındağ et al. (2018) appears somewhat problematic. The TURKSTAT Household Labor Force Survey data they use reports missing wage data (for those not currently employed) as "0" in certain years and as missing in other years. Without accounting for this, we can qualitatively reproduce Altındağ et al. (2018)'s results using their methodology. However, the results change qualitatively, once it is accounted for (by replacing all missing wage observations with 0 or by removing all 0's).
[7] An earlier version of the current paper is cited by Aksu et al. (2018).

Akgündüz et al. (2018) investigates total firm entry in the treated provinces. They employ both a difference-in-differences set-up and the synthetic control method. The treated provinces are the ones geographically close to the Syrian border who received Syrian refugees in 2012 and onwards. The control regions are the rest of the Eastern provinces neighboring the treated regions. They find that the total firm entry does not seem to be significantly affected. However, they find a substantial increase in the number of new foreign-owned firms.

We improve upon these studies in three respects: First, we consider wage and employment effects of the migration arising from its labor demand as well as labor supply effects, as detailed below. We combine the effects of the migration on local economies with those on the native workforce in our analysis; thus we provide a more comprehensive picture on the impact of the Syrian forced migration. Second, we employ the Generalized Synthetic Control (GSC) method developed by Xu (2017) in addition to the traditional difference-in-differences and two-stage least squares estimators. This allows us to (i) eliminate pre-existing trends of any functional form in the data using a data-driven procedure, and (ii) transparently present the dynamic nature of the effects. In this regard, the GSC allows us to address regional economic trends and business cycles without including proxy controls (e.g. regional trade volume) that are potentially affected by the Syrian migration, without arbitrarily determining certain regions (e.g. neighboring regions) as better controls than others, and without including region-specific trends that may yield biased estimates when the effects are dynamic (Meer and West 2016). Second, we correct standard errors for serial correlation as detailed below. Except for Akgündüz et al. (2015) and Akgündüz et al. (2018), none of these studies account for serial correlation and they use heteroskedasticity robust standard errors or they cluster the standard errors at region-by-time level for testing purposes. However, as shown by Bertrand et al. (2004) this leads to over-rejection of the null hypothesis, and produce too narrow confidence intervals.

## Conceptual Framework

Migration waves result in labor supply and labor demand shifts. These effects pull the native workers' employment and wages in opposite directions. The Syrian migration to Turkey increases the labor supply of lower skilled workers. This might lead Turkish and Syrian workers to compete for jobs. According to the descriptive demand-supply framework, this would indicate a rightwards labor supply shift, which pulls the equilibrium wage downwards. It is likely that part of the wage decline will be absorbed by a decline in natives' employment. Thus, the labor supply effect of the migration is to decrease similarly skilled Turkish workers' wages, and potentially employment.

On the other hand, migration-induced demand channels cause a rightwards shift in the labor demand, tend to partly or wholly counteract the labor supply shock. We assess presence of three of these channels in Turkey. The first channel is the native-migrant complementarity (Peri and Sparber 2009, Ottaviano and Peri 2012). If natives and migrants in the same skill level possess different abilities and can perform different tasks, the competition for jobs might be considerably less severe, and even cooperation may take place. The potential adverse effects of the migration might not be as great as when they are perfectly substitutable.

To examine this channel, the share of formally employed LTHS workers is particularly relevant in our case due to the legal status of the migrants. They cannot work formally and informal employment in Turkey is highly common in low-skilled manual task intensive jobs, such as in agriculture and construction (Tansel and Kan 2012). Thus, a rise in the formal employment among the native LTHS workers would suggest existence of this channel.

The second channel is the housing demand channel (Howard 2017). This channel is also highly relevant for the current case, as the Temporary Accommodation Camps in Turkey provide shelter to less than 10% of the migrants. Hence, most of them meet their accommodation needs with their own means. In other words, the housing demand would likely rise with the migration. This, in turn, would lead to a boom in the residential construction industry.

The third channel is the business creation channel (Kerr and Kerr 2011). With the Syrian migrant workers come the regional demand boost and Syrian entrepreneurs. The demand boost might attract entrepreneurs from all nationalities to start new businesses. In addition, Syrian entrepreneurs have fewer opportunities due to the war in the origin country, thus they are more likely to invest in the destination country.

All of these channels increase the demand for native workers. For the native LTHS workers, the main effect of the migration-induced demand boost would be to counteract the labor supply shock. The native HSG workers, on the other hand, would have their wages and/or employment increased compared to the counterfactual case without a migration shock. Therefore, ignoring the demand channels can result in incomplete theoretical models that over-predict the potential adverse effects of the migration on the native workforce.

## Data

**Syrian Migrants** We obtain the data on the number of Syrian guests in Turkey from the Ministry of Interior Directory General of Migration Management (MoI) database.[8] The available data on the total number of the Syrian migrants in Turkey starts from 2011, the first year of the Syrian Civil War. Since 2015, MoI reports the number of the Syrian migrants at province level; and their age and educational distribution at national-level.[9]

[8] We provide detailed variable descriptions and data sources in Appendix A.
[9] In 2014, the Ministry of Interior made a public statement on the number of Syrian guests in each province. Although the relative Syrian densities in the statement is highly similar to the recent data, the figures are too round to be exact.

**Native Labor Force and Labor Market Outcomes** We obtain the data on the labor market outcomes of native workers from Household Labor Force Survey (HLFS) published by TURKSTAT, the official statistical institute of Turkey. We use the data from 2004 to 2015, and it includes 3,921,420 individuals aged between 15-64.[10] It is annual data and reports employment status, monthly wage, demographic characteristics of individuals, social security coverage, and residency at NUTS-2 level. The demographic characteristics include 10 age groups ([15,20), [20,25),…,[60,65)), 3 education levels (less than middle school, less than high school, high school graduate and above), and two genders (male and female). The social security variable, along with the employment status variable, allows us to determine whether an individual is formally or informally employed; as, according to the Turkish Law, every formally employed individual must have social security coverage. Thus, we know with certainty that a worker with no social security coverage is informally employed.

Following the literature (e.g. Card and Peri 2016), we aggregate the individual-level annual data at NUTS-2-by-year level, obtain employment counts, then normalize them by regional pre-treatment (2011) population. The primary motivation behind this is to be able to construct a dependent variable that is not affected by local population changes due to the migration.[11]

Similarly, following the literature (e.g. Borjas 2015), in examining the wage effects of the migration, we partial out the demographic effects and use the residuals. More concretely, we time-

We should re-emphasize that the data is not very reliable prior to the date when the government started to distribute the identity cards to the Syrian forced migrants

[10] Due to the political turmoil in Turkey in 2016 and onwards, we do not include those years.

[11] We note that using individual-level employment indicator as the outcome variable is equivalent to using employment/population. Therefore, estimates from regressions with individual-level data might be affected by changes in population due to internal migration of natives as well as employment.

demean the log-transformed monthly wage variable at individual-level for each age-by-education-by-gender group. Then, we collapse the data at NUTS2-by-year level.[12]

**Housing Demand** In examining the housing demand effects, we use the administrative 2004-2015 province-level new residential building permits data. The data is published by TURKSTAT. Due to the fact that it is administrative; it does not include squatter housing, which is likely common among low-income households. Thus, our estimates may constitute a lower-bound since an increase in squatter housing demand is not directly visible to us.

**Firm Formation** We use the administrative province-level data on new firm establishments published by The Union of Chambers and Commodity Exchanges of Turkey (TOBB). Since 2010, TOBB collects and reports province level information on new company establishments and their start-up capital on behalf of TURKSTAT. The data on new company establishments starts from 2009 and the data on start-up capital investment from 2010. We also acquire information on the total amount of new Syrian co-founded firms and the capital invested in Turkey from the same source.

Table 2 summarizes the data on the native employment and wages, residential permits, and new firm establishments. In the table, we divide the sample into six subsamples, according to the ratio of Syrian migrant population to natives in 2015 (less than 2%, between 2% and 10%, and more than 10%) and the period (2004-2011 and 2012-2015). Presenting the summary statistics in this way allows us to display the changes as well as the levels of the outcomes of interest by the treatment intensity. Thus, one could carry out a simple difference-in-differences analysis using the numbers reported.

[12] We also examine different demographic groups separately in our regressions, thereby implicitly control for demographic factors.

Table 2 shows that in terms of the overall native population, the regions with high and low Syrian density are similar. Employment rate, on the other hand, is remarkably lower in the high Syrian density regions than others before 2012. Decomposing it into formal and informal employment rates reveals that the discrepancy is primarily due to the share of formally employed workers. The share of individuals that are formally employed is considerably lower in the high Syrian density regions. More than two thirds of workers in these regions are informally employed, whereas this number is below 50% in other columns. This partly explains the pre-2012 average wage differences across regions. The employment rates and wages have considerably increased; and the informal employment rate has declined after 2012 in all region groups.

The new building, and new firm statistics reveal that the size of the economic activity is similar in high and low Syrian density regions, and remarkably larger in the medium density regions.[13] Comparing pre-2012 years with 2012-2015, we observe considerable changes in the residential building statistics for all the region groups. In addition, the table shows that the percentage increase in the number of new building permits appears to be positively correlated with the Syrian density. The new firm statistics also shows a similar pattern, where the changes for the high and medium Syrian density regions are always larger than the low Syrian density regions.

## Econometric Framework

One of the challenges in establishing a causal relationship between an outcome of interest and the migration is that certain regions might be able to better absorb the labor supply shocks due to factors unrelated to the migration, such as underlying regional economic trends or business cycles.

[13] The latter is primarily due to Istanbul and Izmir, two provinces whose combined gross provincial products amount to more than 35% of Turkey's GDP.

If this is known by the migrants, they are likely to move to these regions. Although this may not be very likely in the current case, since the migration reason is the war in the origin country, there is no guarantee that the economic trends of destination regions are similar to the rest of the country. Thus, a naïve empirical model that does not account for these factors might confound the latter with the effects of the migration. To address this issue, we employ factor-based approaches.

In the presence of unobserved time varying confounders, such as regional trends, the identifying assumption of difference-in-differences estimators, namely the parallel trends assumption, might be violated. The factor-based models, arguably, overcome this problem by purging the patterns in the error term that can be formulated as interactions of region-specific intercepts (factor loadings, $(\lambda_i)$) and time varying coefficients (latent factors, $(f_t)$).

More specifically, the models we estimate are as follows:

$$Y_{i,t} = \delta T_{i,t} + \boldsymbol{\lambda_i} \boldsymbol{f_t} + \mu_i + \kappa_t + \varepsilon_{i,t} , \tag{1}$$

where $i$ indicates region or province, $t$ year, and $Y_{i,t}$ the outcome variable. $T_{i,t}$ is the variable of interest. $\mu_i$ and $\kappa_t$ are region and year fixed effects. The coefficient of interest is $\delta$ that report the effect of the migration. We also show the dynamic effects, and in those cases, $\delta$ is a vector that can be written as $\delta_t$. $\boldsymbol{f_t}$ are time-variant factors and $\boldsymbol{\lambda_i}$ are region-specific factor loadings. The latter two terms are the variables that turn the standard fixed effects models into factor-based approaches.

**Least-Squares and Two-Stage Least-Squares Estimators (OLS and 2SLS):** As proposed by Zipperer (2016), one method to construct the factors and their loadings is using pre-treatment regional industry-specific employment shares as the factor loadings and interacting them with year fixed effects. This allows each industry to follow a different trend of any functional form, while the intensity of the industry-specific trend in affecting the outcome variable is determined by the pre-treatment employment share of the industry.[14] Thus, these variables account for underlying pre-existing industry trends, and purge them while estimating $\delta$.

Following this idea, we create 2004-2005 NUTS-2 level employment shares of 9 single-digit NACE-1 industries in Turkey and interact them with the year fixed effects.[15] Thus, we allow each industry to follow a different trend, and these trends are important to each region according to the pre-treatment employment shares. Because the loadings belong to the pre-treatment periods, they cannot be affected by the migration wave. Hence, they are not "bad controls"; because they do not eliminate one of the channels that the migration might affect the regional economy.

In addition to the least squares estimators (OLS), we also employ two-stage least squares (2SLS) estimators where we use two instruments. The first instrument is a border indicator. The second one is the predicted Syrian migrant distribution according to the regional Arabic speaking population in 1965 Census.[16] As we show below, the proximity to Syria, and established networks by older generations are important factors for the migrants in choosing their residences (instrument relevance). In addition, both variables are independent of current regional economic trends (instrument exogeneity).

In these specifications, as the variable of interest $T_{i,t}$, we use a continuous variable. The variable takes on the value of 0 for all periods before 2012, since there is no Syrian forced migrant before 2012. For 2012 and onwards, this variable is the share of Syrian migrants in region $i$ in 2015

[14] Put concretely, if an industry is non-existent in a region, then $\lambda_i = 0$ for the region. Thus, the region will not be affected by the trend of the industry. Similarly, a high $\lambda_i$ means that the trend of the industry has a larger impact on the outcome for the region.

[15] Using other years have minimal effect on the results.

[16] This is calculated as $(Predicted\ Syrian\ migrant)_i = \frac{(Arabic\ Speaking\ in\ 1965)_i}{\sum_i (Arabic\ Spearking\ in\ 1965)_i}\ x\ (Syrian\ forced\ migrants)_t$. 1965 is the final year where Census included a mother tongue question.

according to the MOI statistics. Thus, $T_{i,t}$ takes only 2 distinct values for each region; 0 during 2004-2011, and a positive value corresponding to 2015 Syrian migrant to native ratio in 2012 onwards. This variable is similar to the one used by Fallah et al. (2019), and it takes into account of regional variation in the migrant density. However, it does not consider the changes within the post-treatment period. Our primary reasons for constructing the variable of interest in this manner is due to the high measurement error in the regional distribution of the Syrian forced migrant in the official statistics prior to 2015. One concern here might be that, the change in the post-treatment periods might contain important information. We address this concern as follows: In the robustness table, we adjust the variable of interest according to the total number of Syrian migrants in Turkey. In other words, we multiply $T_{i,t}$ by the ratio of the number of Syrian migrants in Turkey in $t$ to that number in 2015. This incorporates the changes in the post-treatment periods. We call this new variable as "adjusted continuous variable of interest".

**Generalized Synthetic Control (GSC) Method:** The method proposed by Zipperer (2016) employs pre-determined employment shares as factor loadings. An alternative to this, as proposed by Xu (2017), is the generalized synthetic control method that allows the data to determine both the factors and the loadings. In other words, it uses the data to find any patterns in the error term. Thus, this method can capture and purge other confounders as well as industry-related trends; thereby it can present more credible estimates. It is our preferred method.

Briefly, the GSC builds upon the interactive fixed effects model of Bai (2009) and combines it with the cross-validation procedure. First, employing the interactive fixed effects model, the factors $(f_t)$ and factor loadings $(\lambda_i)$ of the control groups are calculated by estimating the model only for the control groups. While this step allows us to obtain the factors, the loadings for the treated units is missing. They are estimated in the second step where we use the estimated factors and only the pre-treatment periods of the treated units. There, we run a regression to estimate the region- or province-specific factor loadings. Finally, to determine the exact number of factors to be purged, we employ a leave-one-out-cross-validation procedure that goes through all the pre-treatment periods of treated groups, and then compares the prediction performances (mean squared prediction errors) of the models with alternative number of factors.

As we noted earlier, the GSC is a factor-based model and it builds on the interactive fixed effects model, not the synthetic control model of Abadie et al. (2010). However, due to the method it employs in obtaining factors and loadings, unlike the OLS and 2SLS models, it requires a strict categorization of treatment and control regions. Thus, in this specification, we use a binary variable of interest that takes on the value of 1 for 2012-2015 in the regions where the Syrian migrant density is high (treated regions in the post-treatment periods); 0 otherwise (control regions, and all pre-treatment periods). We define regions or provinces where the migrant density is more than 10% in 2015 as the treated regions. For the purpose of creating sharp differences in terms of the migrant density between control and treatment regions, we exclude 7 NUTS-2 regions or 14 provinces where the Syrian migrant share is between 2% and 10% in our main analyses.[17]

**Robustness Checks:** We make certain choices in our model specifications. To show that these choices do not affect the findings in a qualitative way we alter these choices and report the results. These robustness checks include using alternative migrant density thresholds (GSC), the border instrument only (2SLS), no factors (2SLS), state-specific linear trends instead of the industry

[17] To make the coefficients comparable, we multiply the estimates obtained by the traditional methods (OLS and 2SLS) by the ratio of the average Syrian migrant share in the high density regions to that in the control regions. Thus, we report: $\delta = \omega_1 * (Syr_{tr} - Syr_{co})$, where $\omega_1$ is the OLS or 2SLS estimate, and $Syr_{tr}$ and $Syr_{co}$ show the ratios of the Syrian migrants to the native population in the treated and control regions.

factors (2SLS), the quadratic term of the variable of interest to capture the non-linear effect (2SLS), and the adjusted continuous variable of interest (2SLS).

**Inference:** There are 81 provinces and 26 NUTS-2 regions in Turkey. Therefore, when the variable of interest, $T_{i,t}$ is defined at NUTS-2 level, in wage and employment regressions, the number of clusters is too low as noted by Angrist and Pischke (2008). This renders the confidence interval estimates to be too narrow. To account for this, we produce p-values that are better suited for testing purposes in these cases. We use the parametric bootstrap method proposed by Xu (2017) in the GSC model, wild cluster bootstrap method (CGM) proposed by Cameron et al. (2008) in the OLS model, wild restricted residual bootstrap (WRR) proposed by Davidson and MacKinnon (2010) in the 2SLS model.

## Findings

### Impact on the Native Workforce

One of the most direct effects of the migration is increasing the labor supply. Assuming that the demand remains constant, the migration causes labor supply to shift rightwards, decreases the wages and, potentially, employment of similarly skilled native workers (Dustmann et al. 2016). In addition, the current debate on the effects of the Syrian migration in Turkey mostly revolves around its impact on the native workforce.

Given the educational characteristics of the Syrian migrants, we begin our examination with how the migration affected lower-skilled (less than high school (LTHS)) native workers' employment and wages. Figure 3, Panel (a) shows that lower-skilled employment has not declined due to the migration. On average, the estimated effect in the post-treatment period is 0.000 (0.047). Their wages (Panel (b)), on the other hand, appears to decline sizably in 2013 and quickly recovers in 2014. On average, native LTHS wages have declined by 2.1% (s.e. 2.5%), though the average estimate is mostly driven by the decline in 2013, hence not precise to reject the null hypothesis of no effect.

In Table 3, we report the estimated employment (Panel A) and wage effects (Panel B) on the native lower- (less than high school) and higher-skilled (high school or above (HSG)) workforce using the GSC, OLS, and 2SLS methods. Column (1) reproduces the estimates of Figure 3. It also shows that 1 and 3 factors are purged in Panels A and B, suggesting a naïve difference-in-differences estimator might fail to produce credible estimates. In column (2), we show the effects on the higher-skilled. Both employment and wage effects appear to be positive and relatively sizable (0.063 (0.047) and 0.057 (0.023)). While we cannot reject the no effect hypothesis for the employment effect, the wage effect of the migration on native HSG workers is statistically significant. This is in line with the documented complementarity between lower-skilled and higher-skilled workers.[18]

Columns (3) -(6) use the 2SLS and OLS specification to estimate the effects on lower-skilled and higher-skilled workers. The findings are qualitatively in line with our preferred estimates. While the native LTHS workers are not adversely affected by the migration, the HSG workers appear to somewhat benefit from the shock. The main quantitative difference between the traditional specifications and the GSC arises when we focus on the native LTHS wages. The traditional models suggest a positive effect on them, while the GSC indicates a small negative effect. We discuss the discrepancy below and in Appendix B in more detail, and favor the GSC estimates in

[18] In Table B3, we show that when we examine demographic groups at more disaggregated levels (teen, male LTHS, female LTHS, less than middle school), the effects remain essentially the same.

this case, as it purges all confounders (not only those related to industry shocks) that may violate the parallel trends assumption.

Therefore, our analysis shows that (i) the native workers that are similarly skilled as the migrants have experienced small and statistically zero wage and employment changes; (ii) wages of the relatively higher skilled native workers have increased as a result of the Syrian migration. In the next subsections, we document channels that create new employment opportunities and enable local labor markets to absorb the shock.

**Demand Channel (1): Native-Migrant Labor Complementarity**

One well-documented channel in the literature is that there is imperfect substitution between migrant and native labor (Ottaviano and Peri 2012). With the arrival of migrants, natives might be able to pursue job opportunities where the migrants cannot be employed. Given that the Syrian migrants cannot formally work, and they are mostly lower-skilled, we ask the following question to document the existence of this channel: Did the entry of the Syrian migrants to the lower-skilled informal labor market in the host regions caused the native LTHS workers to move towards formal jobs?

Figure 4 Panel (a) confirms the presence of the channel. The share of formally employed native LTHS workers has increased rapidly starting from 2013.[19] On average, the share has increased by 3.3% (2.3%) due to the migration in the post-treatment periods.

[19] Note that our argument that the change in the formally employed native LTHS workers is due to the migration would not be necessarily true if the group's skill composition changes. To address this, in the Appendix, we also examine how employment rates of sub-groups of the native LTHS changes due to the migration. In none of the cases we find an indication of a decline in employment impact.

Table 4 column (1) reproduces the estimates in Figure 4. Columns (3) and (5) use the traditional models and confirms that the migration caused the native LTHS workers to find employment in formal jobs.

Alternatively, one can examine the share of workers earning at least 100% of the statutory minimum wage. Since the minimum wage is not binding for informally employed workers, a rise in the share of formally employed workers would increase the share of workers earning at least 100% of the minimum wage.

For this purpose, we construct a binary variable that takes on the value of 1 for all workers earning at least the minimum wage, 0 otherwise. Then we partial out all the demographic effects on it by using a procedure similar to the one used in the wage regressions, and time-demean for each age-by-education-by-gender group.

Table 4 columns (2), (4) and (6) show the percentage point change in the share of workers earning at least the minimum wage in the host regions. We observe a statistically significant increase of more than 2.5 percentage points in all columns. This suggests that compared to the counterfactual case where there is no migration, 2.5 percentage points more native workers in the host regions are earning at or above the minimum wage.

Figure 4 Panel (b) extends the analysis to other threshold values to depict a more comprehensive picture of how the migration affected wage distribution in the host regions. We examine the changes in 8 threshold values: 50%, 100%, …, 400% of the minimum wage. The figure delivers two new information about the effects of the migration: First, the migration has increased the share of workers earning upper-middle income. The shares of workers earning at or above 200% and 250% of the minimum wage have increased by 2.11 and 2.19 percentage points. These findings are in line with the finding of a positive wage effect on the native HSG workers in Table 3. They show that the Syrian migrant and the relatively high skilled native labor are complementary. Second, the migration had almost no effect on very-high-wage workers in the treated regions. This suggests that the lower-skilled migration has no effect on the very high skilled workers.

**Demand Channel (2): Housing Demand**

The second channel that is particularly relevant in the current case is that the arrival of migrants causes a housing demand boost (Howard 2017). As more than 90% of the Syrian migrants reside outside the Temporary Accommodation Camps, an overwhelming majority of them cover their accommodation expenses through their own means. We expect this to lead a dramatic increase in the new residential building demand.

Figure 5 shows that the number of new dwelling unit permits has increased quite rapidly since 2012, the first year of the migration wave.[20] The rise appears to reach its peak point in 2014, the year when more than 1 million Syrian forced migrants entered Turkey. On average, the estimated effect is 0.337 (0.121), indicating a massive boom in the residential construction industry.

Table 5 reproduces the findings reported in Figure 5, and, in addition, employs alternative measurement units (squared meter, dwelling unit, and new buildings), and 2SLS (columns (4) - (6)) and OLS (columns (7) -(9)) models as well as the GSC model (columns (1) -(3)) to estimate the impact of the migration on the residential building permits. In columns (1), (4), and (7), we use squared-meter, while columns (2), (5), and (8) use dwelling units, and the remaining columns use number of buildings as the measurement unit. All columns report a sizable positive effect. When we focus on the change in the number of dwelling units in columns (2), (5), and (8), we see that

[20] The outcome variable is the number of building permits normalized by pre-treatment (2011) provincial GDP. We calculate the percentage change by dividing the estimate by the mean of the dependent variable.

the point estimates suggest an increase larger than 33.6% and they are all statistically significant. Other columns qualitatively confirm this finding.

**Demand Channel (3): Increased Entrepreneurial Activities of Syrians and non-Syrians**

Another channel through which we observe the demand effect of the migration is the new firm formation. Migrants might bring capital to the destination country and start their own businesses. Moreover, the migration-induced regional demand might attract capital and lead to increased new firm formation (Baptista et al., 2008; Karahasan, 2015; Van Stel and Suddle, 2008).

In Figure 6 Panel (a), we report the change in the number of new firms with at least one Syrian co-founder between 2010 and 2015. The figure shows that while there are fewer than a hundred new Syrian cofounded firms prior to 2012; this number is 1,599 in 2015. In the right-hand side panel (Panel (b)), we normalize the number by dividing it to the total number of firms co-founded by at least one non-native. It shows that the share was less than 2.3% in 2011 and 2010, and it has increased to more than 31.9% in 2015. In addition, the shapes of the graphs in both of the panels are quite similar to the one in Figure 1, where we report the total number of Syrian forced migrants in Turkey. This suggests that the evolution of the total number of the migrants in Turkey is a good predictor for the time path of the Syrian entrepreneurial activities.

However, it is not only the Syrians who founded new firms in the host regions. As shown in Table 6, the number of new firms has increased by 17.4% according to the 2SLS model and by 13.2% in the OLS models. Even when we exclude all firms with at least one Syrian co-founder, we still observe a sizable increase of around 10%, suggesting that non-Syrian entrepreneurs also benefited from the migration.[21]

[21] We cannot employ the GSC model here, as the number of pre-treatment periods is too few (only 2 years) to estimate both the factor loadings and the factors.

To summarize, our empirical examination yields that local labor markets in Turkey have been able to absorb approximately the part of the 2.5 million lower-skilled and non-Turkophone Syrian nationals who entered the local labor markets. Given the size of the labor supply shock, this can only be explained by a counteracting migration-induced demand boost. We document that three of these demand channels are native-migrant labor complementarity, housing demand boost, and increased entrepreneurial activities of Syrians and non-Syrians.

**Robustness of the Main Results**

There are certain choices we make throughout our empirical analysis. In Table 7, we show that alternative choices do not change the results qualitatively.

In columns (1) and (2), we alter the way we define treated and control regions in the GSC model. In our preferred specification, we define regions where the number of Syrian migrants is less than 2% of the native population as control regions; while treated regions are those where this ratio is at least 10%, and the remaining regions are excluded. In column (1), we include these excluded regions in the control group, and in column (2), we include them in the treated group. In all cases, the estimates confirm our findings that the migration did not lead to large employment or wage losses for the native lower-skilled workers. It increased the share of formally employed workers, it was beneficial for the native higher-skilled workers, and it caused a housing demand boost and a rise in new firm formation.

In columns (3) -(7), we try alternative versions of the 2SLS model. Due to the fact that the ethnic distribution variable in the 1965 Census potentially may suffer from the measurement error, we use only the border indicator as the instrument in column (3). In column (4), we do not augment the model with factors, and utilize equation (1) without the $\boldsymbol{\lambda_i}$ and $\boldsymbol{f_t}$ terms. In column (5), we replace these terms with NUTS-2- or province-specific linear trends. In column (6), we augment equation (1) with the quadratic term of the variable of interest ($T_{i,t}^2$). For this purpose, we add a third instrument for the non-linear term, following the suggestion in Wooldridge (2010). We create the third instrument as follows: First, we predict the relative supply shock using our exogenous variables. Then, we create a variable by taking the square of the predicted values and include it in the set of instruments. By construction, this instrument is able to retrieve the non-linear exogenous component, and it satisfies the exogeneity assumption as long as other instruments do.[22] If considerable differences occur between estimated effects obtained from this specification and our main estimates, then this implies non-linearity. In column (7), we use the adjusted variable of interest.

The first row in Table 7 shows the estimates for the change in the native LTHS employment rate. All the columns indicate that the change is very small, the point estimates are between -0.010 and 0.016, and statistically indistinguishable from zero.

The second row is the change in the native HSG employment rate. Although on average the point estimates are larger than the ones in the first row; they take positive or negative values, depending on the specification.

The third and fourth rows show the percentage change in the native LTHS and HSG wages. For the former, the GSC and the 2SLS models yield conflicting results. While the GSC argues that there is a small decline, the 2SLS model claims that the shock has been relatively positive. This discrepancy is expected and similar to the one in Table 3. As shown in Appendix B, it is likely due to the fact that the OLS and 2SLS models suffer from pre-existing trends and yielding biased estimates in this case. When we focus on the native HSG wages, we find that there is an agreement

[22] To be able to compare the estimate obtained using the quadratic specification with others, we use the following algebraic manipulation: $\delta = \omega_1 * (Syr_{tr} - Syr_{co}) + \omega_2 * (Syr_{tr}^2 - Syr_{co}^2)$, where $\omega_1$ and $\omega_2$ are the estimates for the linear and non-linear terms.

across columns. All the specifications indicate a positive increase, and most of them are statistically significant at 10% level.

In the last three rows, we assess the robustness of the estimates related to the demand channels. Respectively, we confirm our arguments that the Syrian forced migration pushed the native LTHS workers to formal employment (native-migrant labor complementarity channel), increased the number of dwelling unit permits (housing demand channel), and the new firm formation (increased entrepreneurial activities channel) in the host regions compared to the counterfactual case where there was no migration.[23]

## Discussion and Conclusion

Our empirical findings have depicted a relatively optimistic scenario in terms of the effects of the migration on the native workers. We find that the native lower skilled workers in Turkey experienced small wage and employment losses after the Syrian migration; while the higher skilled workers have seen gains. To explain these, we documented the presence of three different demand channels; namely (i) the native-migrant labor complementarity, (ii) increased housing demand and (iii) increased entrepreneurial activities in the host regions.

One question at this point is whether and by how much the empirical findings and the predictions of the canonical economic model presented in Borjas (2013) can be reconciled. As we detail in Appendix C, the canonical model that assumes away the above-mentioned demand channels and considers immigration merely as a labor-supply shock over-predicts the adverse effects on the

[23] In examining the percentage change in the number of new firms, we do not report the GSC estimates as the number of pre-treatment periods is too small. Although remains estimable, this issue causes the specification with province-specific linear trends relatively imprecise, as there are only two years for the estimation of the trends.

native workers. It predicts that between 2011 and 2015, the wages of the native lower-skilled workers in the host regions should experience a wage decline of 4%, while our empirical findings suggest that the change is substantially smaller. Therefore, we conclude that omitting migration-induced demand effects in theoretical models likely leads to incorrect and relatively pessimistic predictions on the effects of immigration.

One precautionary note here is that our findings apply mostly to the short run effects of the Syrian migration on native workers. There is reason to believe that its long run effects might be different. On the one hand, the labor force participation of the Syrian migrants might increase over time, and, as a result, the labor supply shock might dominate the labor demand effects. On the other hand, theoretically, the potential adverse effects of the migration on native workforce is smaller in the long-run, since capital tends to accumulate in host regions, which, in turn, pulls wages upwards. In addition, in the long run, it possible that the increase in supply of low-skilled workers alter technology choices in the industries in the host regions. Providing answers for these questions are beyond the scope of the current paper, and present an agenda for future research.

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## TABLES

### Table 1: Characteristics of the Syrian migrants, and natives

| | Syrian migrant (Age: 15+) | Native (Age: 15-64) | Native (Age: 15-64) |
|---|---|---|---|
| **Educational Attainment** | | | |
| No degree | 0.623 | 0.116 | 0.234 |
| Primary School | 0.215 | 0.321 | 0.280 |
| Secondary School | 0.086 | 0.224 | 0.252 |
| High school | 0.047 | 0.191 | 0.143 |
| Some college and above | 0.027 | 0.148 | 0.092 |
| **Age groups** | | | |
| 15-18 | 0.182 | 0.123 | 0.176 |
| 19-24 | 0.189 | 0.106 | 0.127 |
| 25-29 | 0.154 | 0.119 | 0.120 |
| 30-34 | 0.129 | 0.124 | 0.116 |
| 35-39 | 0.095 | 0.117 | 0.104 |
| 40-44 | 0.069 | 0.107 | 0.099 |
| 45-49 | 0.055 | 0.089 | 0.078 |
| 50-54 | 0.044 | 0.088 | 0.075 |
| 55-59 | 0.030 | 0.070 | 0.056 |
| 60-64 | 0.021 | 0.058 | 0.050 |
| 65+ | 0.032 | - | - |
| **Gender** | | | |
| Man | 0.531 | 0.501 | 0.490 |
| Woman | 0.469 | 0.499 | 0.510 |
| **Regions:** | All | All | Syr./Nat. > 10% |

*Notes.* The first column reports the demographic characteristics of the (15+) Syrian migrants in 2015. For comparison, we also provide comparable numbers for all (15-64) natives, and the (15-64) natives in the regions where the ratio of Syrian migrant population to natives (Syr./Nat.) is at least 10% calculated from the 2015 TURKSTAT Household Labor Force Survey. Data on Syrian migrants is from the Ministry of Interior Directory General of Migration Management.

## Table 2: Descriptive statistics

| Variables | Pre-2012 Averages | | | 2012-2015 Averages | | |
|---|---|---|---|---|---|---|
| | Syr./Nat. > 10% | 10% ≥ Syr./Nat. ≥ 2% | 2% > Syr./Nat. | Syr./Nat. > 10% | 10% ≥ Syr./Nat. ≥ 2% | 2% > Syr./Nat. |
| **Labor Force Statistics** | | | | | | |
| Working age population | 1,559,380 | 2,833,012 | 1,323,757 | 1,832,563 | 3,135,181 | 1,444,050 |
| Employment rate | 0.366 | 0.435 | 0.488 | 0.393 | 0.487 | 0.528 |
| Formal employment rate | 0.138 | 0.280 | 0.253 | 0.198 | 0.357 | 0.321 |
| Informal employment rate | 0.228 | 0.155 | 0.235 | 0.195 | 0.130 | 0.207 |
| Employment rate of LTHS | 0.335 | 0.379 | 0.448 | 0.354 | 0.418 | 0.479 |
| Average wage (in 2010 TL) | 793.182 | 1,013.708 | 992.321 | 944.653 | 1,146.054 | 1,125.238 |
| Average wage in informal employment (in 2010 TL) | 486.547 | 632.988 | 541.072 | 558.988 | 630.005 | 593.086 |
| Average wage of LTHS (in 2010 TL) | 596.169 | 744.461 | 711.090 | 684.889 | 797.797 | 778.216 |
| **Building Statistics** | | | | | | |
| Resid. building permits ($m^2$) | 816,598 | 2,639,413 | 768,649 | 2,219,706 | 4,086,398 | 1,127,139 |
| Resid. building permits (# dwelling units) | 4,798 | 17,219 | 5,043 | 12,872 | 26,465 | 7,086 |
| Resid. building permits (# buildings) | 689 | 2,509 | 841 | 1,148 | 2,999 | 910 |
| Resid. occupancy permits (# dwelling units) | 2,383 | 8,414 | 3,635 | 7,005 | 20,114 | 6,051 |
| **New Firm Statistics** | | | | | | |
| # New firm establishments | 470.600 | 1,988.667 | 303.699 | 563.250 | 2,246.107 | 303.544 |
| Start-up capital investment (in 2010 mln. TL) | 173.547 | 667.043 | 79.246 | 133.015 | 435.109 | 53.020 |

*Notes.* The table reports the mean values for the outcomes. The sample is divided into 6, according to the relative size of the supply shock (the ratio of Syrian forced migrant population to natives, Syr/Nat.), and the time dimensions. Pre-2012 corresponds to 2004-2011, 2009-2011, and 2010-2011 for labor and building statistics, the number of new firm establishments, and the total start-up capital investment, respectively. Labor statistics are from the TURKSTAT Household Labor Force Survey, building statistics from the TURKSTAT, and new firm statistics from TOBB.

**Table 3: Employment and wage effects of the Syrian migration by skill groups**

| | Generalized Synthetic Control | | 2SLS | | OLS | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: Employment | | | | | | |
| Change in employment rate | 0.000 | 0.063 | -0.000 | 0.060 | -0.002 | 0.053 |
| | (0.047) | (0.047) | (0.036) | (0.057) | (0.029) | (0.054) |
| P-value | 0.991 | 0.286 | 0.984 | 0.292 | 0.940 | 0.510 |
| Unobserved factors | 1 | 0 | - | - | - | - |
| Panel B: Wage | | | | | | |
| % change in wages | -0.021 | 0.057 | 0.051 | 0.049 | 0.072 | 0.055 |
| | (0.025) | (0.023) | (0.033) | (0.026) | (0.030) | (0.021) |
| P-value | 0.396 | 0.011 | 0.108 | 0.064 | 0.080 | 0.084 |
| Unobserved factors | 3 | 2 | - | - | - | - |
| # clusters | 19 | 19 | 26 | 26 | 26 | 26 |
| # treated clusters | 3 | 3 | - | - | - | - |
| Observations | 228 | 228 | 312 | 312 | 312 | 312 |
| Groups: | LTHS | HSG | LTHS | HSG | LTHS | HSG |

Notes: The table reports the change in the employment rate and percentage change in the (residual) wages of the natives with no high school diploma (LTHS) and of natives with at least high school degree (HSG), using the 2004-2015 NUTS-2-by-year aggregated TURKSTAT Household Labor Force Survey. The dependent variables are the LTHS, and HSG employment counts normalized by 2011 population of the demographic group. Columns 1 and 2, 3 and 4, and 5 and 6 use the GSC, the 2SLS, and the OLS models, respectively. The standard errors are clustered at NUTS-2 level. For testing purposes, the p-values produced by the parametric bootstrap technique of the GSC, the wild cluster bootstrap (CGM), and the wild restricted residual bootstrap (WRR) are reported for inference. Columns 1 and 2 report the number of unobserved factors purged by the GSC. Hansen's J statistics are insignificant at conventional levels and the F statistic of the first stages are greater than 10 in columns 3 and 4.

**Table 4: Change in the shares of formally employed native LTHS workers and workers earning at or above minimum wage (MW)**

| | GSC | | 2SLS | | OLS | |
|---|---|---|---|---|---|---|
| | 1* | 2** | 3* | 4** | 5* | 6** |
| Percentage point change | 0.033 | 0.025 | 0.100 | 0.029 | 0.084 | 0.084 |
| | (0.023) | (0.013) | (0.021) | (0.016) | (0.023) | (0.023) |
| P-value | 0.067 | 0.051 | 0.000 | 0.128 | 0.004 | 0.004 |
| Unobserved Factors | 2 | 0 | - | - | - | - |
| # clusters | 19 | 19 | 26 | 26 | 26 | 26 |
| # treated clusters | 3 | 3 | - | - | - | - |
| Observations | 228 | 228 | 312 | 312 | 312 | 312 |

*: Share of native LTHS that are formally employed; **: Share of workers earning at or above 100% of the MW.
Notes: The table reports the percentage point changes in formal employment shares of the natives with no high school diploma (LTHS), and in the shares of workers earning at or above the MW after the migration shock, using the 2004-2015 NUTS-2-by-year aggregated TURKSTAT Household Labor Force Survey. The standard errors are clustered at NUTS-2 level. For testing purposes, the p-values produced by the parametric bootstrap technique of the GSC, the wild cluster bootstrap (CGM), and the wild restricted residual bootstrap (WRR) are reported for inference. Columns 1 and 2 report the number of unobserved factors purged by the GSC. Hansen's J statistics are insignificant at conventional levels and the F statistic of the first stages are greater than 10 in columns 3 and 4.

**Table 5: Effects of the Syrian migration on Residential Construction Sector**

| | Generalized Synthetic Control | | | 2SLS | | | OLS | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| % change in building permits | 0.497<br>(0.107) | 0.337<br>(0.121) | 0.246<br>(0.147) | 0.523<br>(0.180) | 0.496<br>(0.128) | 0.337<br>(0.071) | 0.314<br>(0.078) | 0.336<br>(0.063) | 0.191<br>(0.101) |
| P-value | 0.006 | 0.006 | 0.008 | 0.005 | 0.000 | 0.000 | 0.000 | 0.000 | 0.061 |
| Unobserved factors | 0 | 2 | 2 | - | - | - | - | - | - |
| # clusters | 67 | 67 | 67 | 81 | 81 | 81 | 81 | 81 | 81 |
| # treated clusters | 5 | 5 | 5 | - | - | - | - | - | - |
| Observations | 804 | 804 | 804 | 972 | 972 | 972 | 972 | 972 | 972 |
| Measurement unit: | $m^2$ | Dwelling unit | Buildings | $m^2$ | Dwelling unit | Building s | $m^2$ | Dwelling unit | Buildings |

Notes: The table reports the percentage change in the residential building permits in the treated regions after the migration shock, using the province-by-year aggregated 2004-2015 TURKSTAT building statistics. The dependent variable is the total new building permits in m2 (square meter), in dwelling units, and in buildings divided by 2011 gross provincial product. Standard errors are clustered at province level or the GSC standard errors are reported. The corresponding p-values are reported for testing purposes. First three columns report the number of unobserved factors purged by the GSC. Hansen's J statistics are insignificant at conventional levels and the F statistic of the first stages are greater than 20 in columns 4 to 6. For better precision, the regressions are weighted by 2011 gross provincial product.

**Table 6: Impact of the Syrian migration on new company establishments**

| | 2SLS | | | | OLS | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| % change | 0.174 | 0.117 | 0.181 | 0.138 | 0.132 | 0.073 | 0.169 | 0.114 |
| | (0.071) | (0.064) | (0.080) | (0.080) | (0.023) | (0.021) | (0.037) | (0.036) |
| P-value | 0.017 | 0.070 | 0.026 | 0.087 | 0.000 | 0.001 | 0.000 | 0.002 |
| # clusters | 81 | 81 | 81 | 81 | 81 | 81 | 81 | 81 |
| Observations | 567 | 567 | 486 | 486 | 567 | 567 | 486 | 486 |
| Syrian share excluded | | Y | | Y | | Y | | Y |
| Outcome variable: | Number of new firms | Number of new firms | Start-up capital | Start-up capital | Number of new firms | Number of new firms | Start-up capital | Start-up capital |

*Notes.* The table reports the percentage change in the new company establishments, and real start-up capital invested in the treated regions after the migration shock, using province-by-year aggregated 2009-2015 and 2010-2015 TOBB firm statistics. The dependent variables are log-transformed number of new company establishments, and log-transformed real start-up capital invested. The even-numbered columns exclude companies with at least one Syrian co-founder, and the Syrian capital. Standard errors clustered at province level, and the corresponding p-values are reported for the precision and the inference.

## Table 7: Robustness of Main Results

| | Generalized Synthetic Control | | 2SLS | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Change in native LTHS employment rate | 0.016 | 0.014 | -0.006 | 0.015 | -0.004 | 0.008 | -0.010 |
| | (0.021) | (0.017) | (0.035) | (0.023) | (0.027) | (0.034) | (0.027) |
| P-value | 0.434 | 0.394 | 0.984 | 0.564 | 0.608 | 0.807 | 0.588 |
| Change in native HSG employment rate | 0.001 | 0.038 | 0.048 | 0.034 | 0.017 | 0.054 | -0.013 |
| | (0.058) | (0.021) | (0.050) | (0.063) | (0.072) | (0.039) | (0.026) |
| P-value | 0.650 | 0.048 | 0.224 | 0.776 | 0.500 | 0.177 | 0.600 |
| Percentage change in native LTHS wage | -0.007 | -0.015 | 0.063 | 0.040 | 0.051 | 0.074 | 0.017 |
| | (0.022) | (0.016) | (0.032) | (0.025) | (0.030) | (0.044) | (0.019) |
| P-value | 0.738 | 0.774 | 0.080 | 0.124 | 0.102 | 0.105 | 0.389 |
| Percentage change in native HSG wage | 0.053 | 0.027 | 0.043 | 0.055 | 0.079 | 0.041 | 0.068 |
| | (0.029) | (0.017) | (0.024) | (0.013) | (0.051) | (0.017) | (0.020) |
| P-value | 0.082 | 0.158 | 0.084 | 0.076 | 0.135 | 0.019 | 0.020 |
| Change in share of formally employed native LTHS workers | 0.029 | 0.019 | 0.095 | 0.061 | 0.042 | 0.092 | 0.064 |
| | (0.017) | (0.013) | (0.022) | (0.021) | (0.030) | (0.025) | (0.014) |
| P-value | 0.040 | 0.085 | 0.000 | 0.116 | 0.010 | 0.001 | 0.000 |
| Number of clusters | 26 | 26 | 26 | 26 | 26 | 26 | 26 |
| Number of treated clusters | 3 | 10 | - | - | - | - | - |

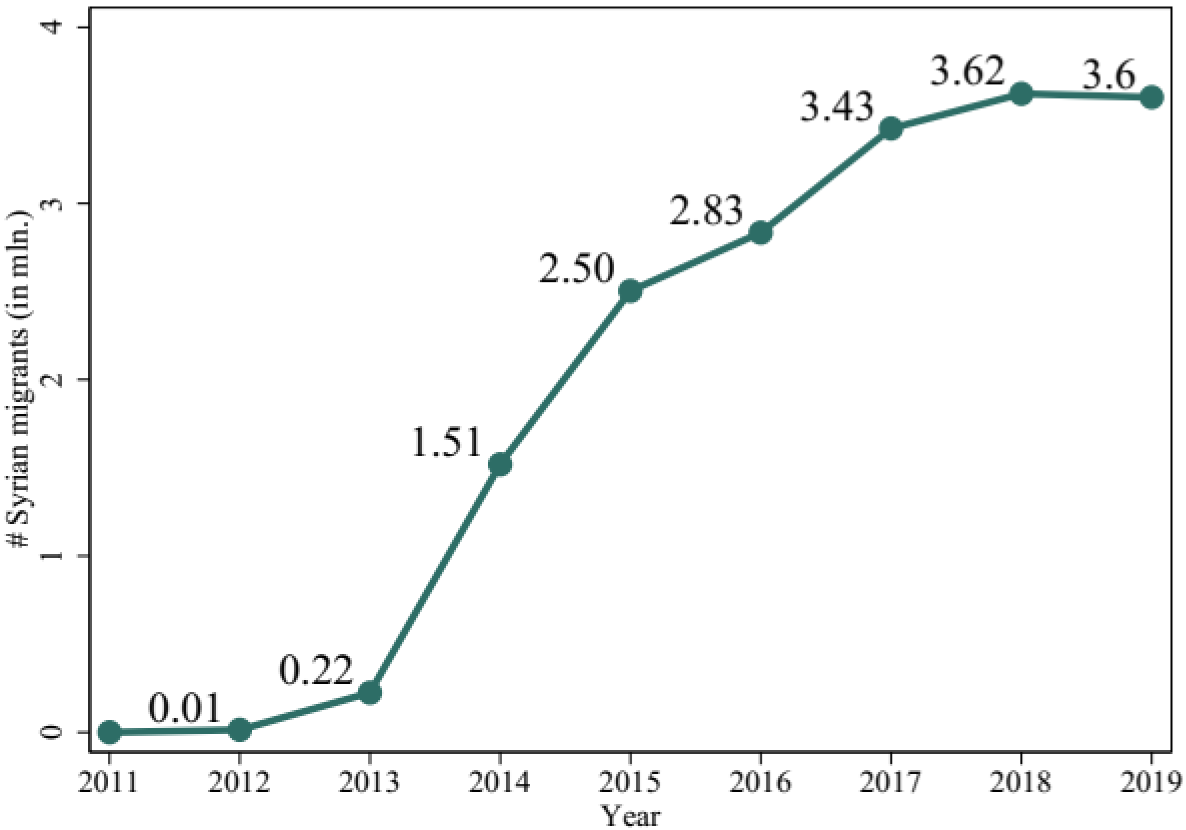
## Table 7 cont'd

| | Generalized Synthetic Control | | 2SLS | | | | |
|---|---|---|---|---|---|---|---|
| Percentage change in dwelling unit building permits | 0.382 | 0.187 | 0.495 | 0.488 | 0.300 | 0.475 | 0.356 |
| | (0.094) | (0.090) | (0.119) | (0.107) | (0.113) | (0.186) | (0.124) |
| P-value | 0.000 | 0.025 | 0.000 | 0.000 | 0.009 | 0.012 | 0.005 |
| Percentage change in number of new firms | NA | NA | 0.192 | 0.191 | 0.182 | 0.232 | 0.155 |
| | | | (0.070) | (0.070) | (0.134) | (0.096) | (0.054) |
| P-value | | | 0.008 | 0.008 | 0.178 | 0.018 | 0.005 |
| Number of clusters | 81 | 81 | 81 | 81 | 81 | 81 | 81 |
| Number of treated clusters | 5 | 19 | - | - | - | - | |
| Specification | Treated > 10% | Treated > 2% | Border instrument only | No additional control | Region-specific trends | Quadratic term | Annually adjusted |

*Notes.* The robustness table assesses the importance of the choices made in the paper while constructing the empirical models. Rows indicate the outcome variables. The columns alter the choices made in building the models. The first two columns present estimates obtained using alternative versions of the GSC models, and the columns (3)-(7) alternative versions of the 2SLS model. Standard errors are clustered at NUTS-2 level when the number of clusters is 26, and at province-level when it is 81. In the first two columns, we report the p-values obtained using the parametric bootstrap technique of the GSC. In other columns, when the number of clusters is 26, we use the wild restricted residual (WRR) method to produce the p-values. Otherwise, we report the cluster robust p-values.

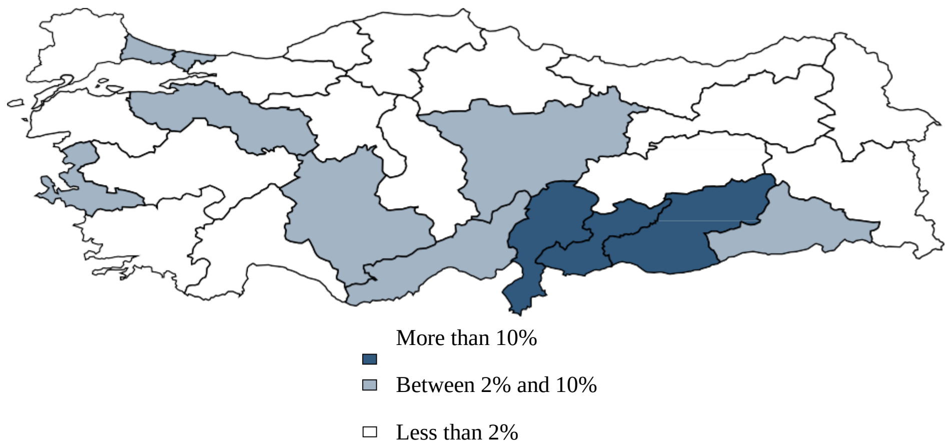
## FIGURES

**Figure 1: Total number of Syrian forced migrants in Turkey**

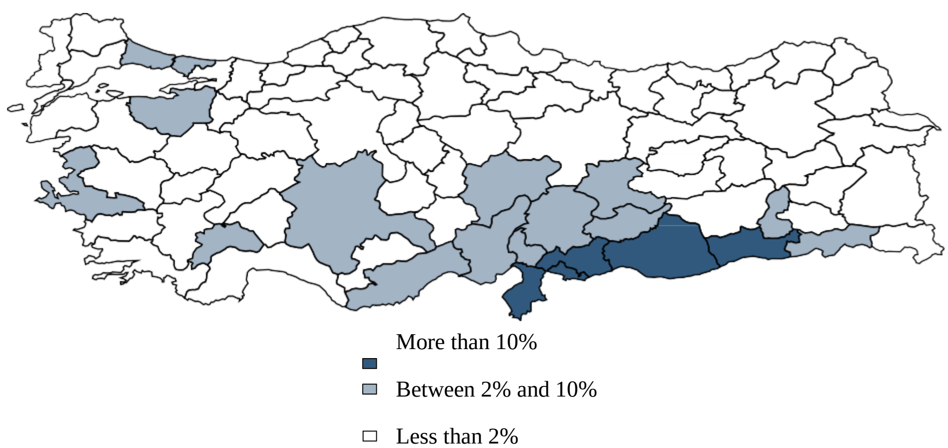



*Notes:* The figure shows the total number of Syrian forced migrants in Turkey between 2011 and 2019. Only Syrian nationals fled their country due to the war are considered. The data provided by Ministry of Interior Directory General of Migration Management is used.

**Figure 2: Regional distribution of the Syrian migrants**



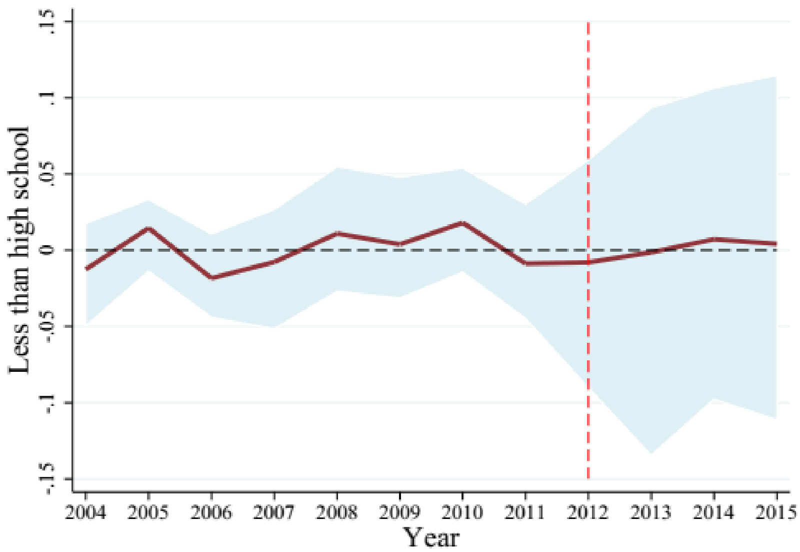

(a) NUTS-2 level



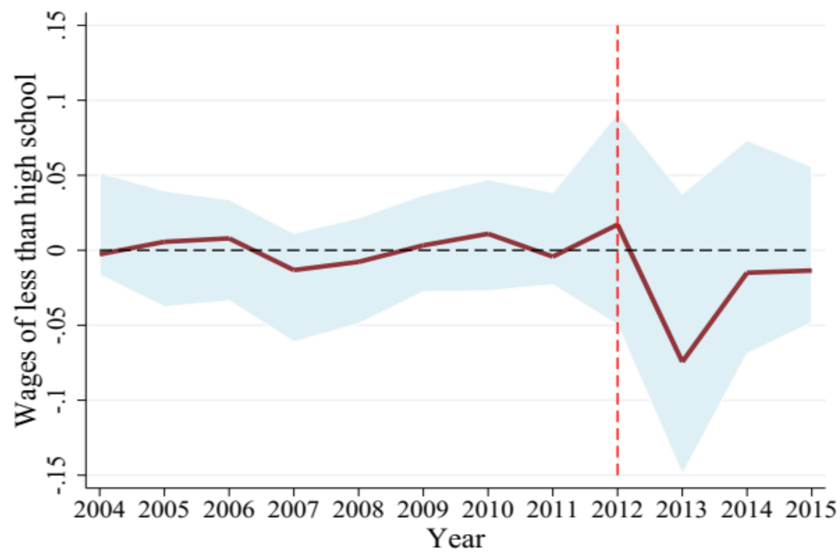

(b) Province level

*Notes:* The graphs plot the NUTS-2 and province-level distributions of the number of Syrian forced migrants as shares of local native population in 2015. Dark areas indicate that the Syrian migrant population is at least 10% of the native population, white areas at most 2%, and the others between 2% and 10%. The data provided by Ministry of Interior Directory General of Migration Management is used.

**Figure 3: Impact of the Syrian migration on native LTHS employment rates and wages over time; the GSC**



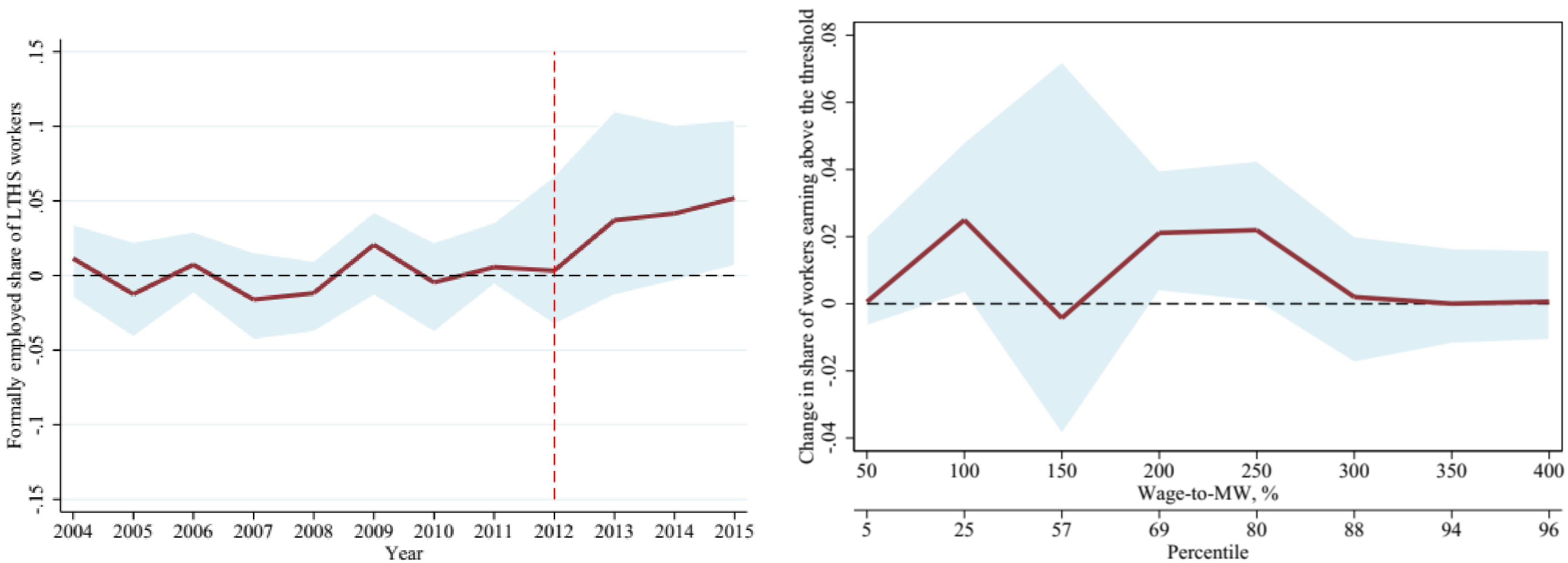

(a)




(b)

*Notes:* Panel (a) plots the change in the native LTHS employment rate in the treated regions compared to the counterfactual. Panel (b) plots the percentage change of the average (residual) wages of the native LTHS workers in the treated regions compared to the counterfactual. Both panels use the 2004-2015 NUTS-2-by-year aggregated TURKSTAT Household Labor Force Survey. The vertical dash lines indicate the first year of the migration shock. The generalized synthetic control method (GSC) is employed. The dotted lines show 95% confidence intervals, calculated using the parametric bootstrap of the GSC.

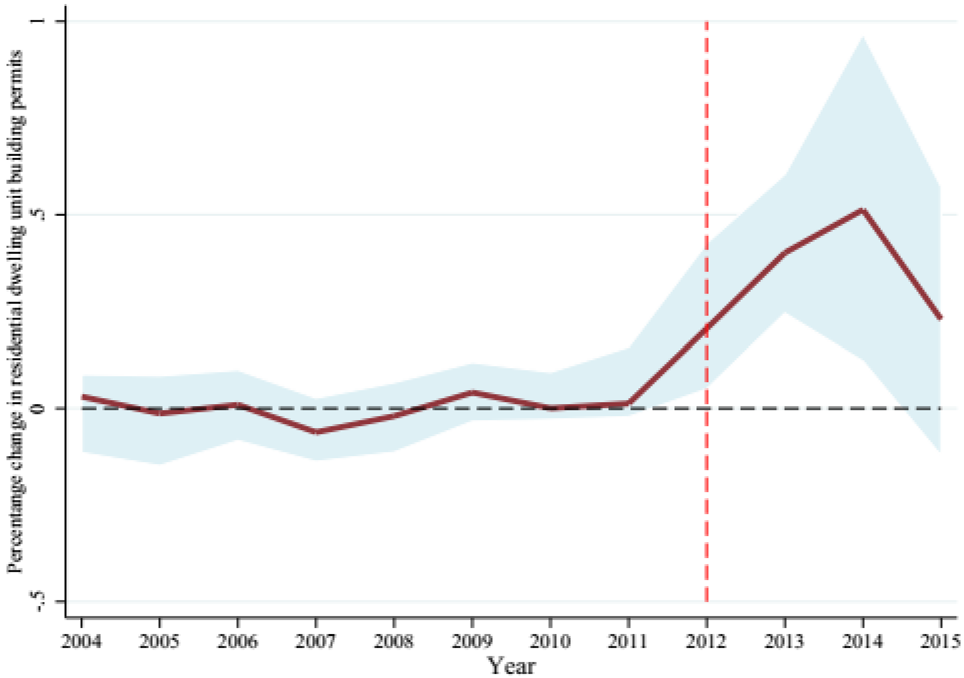
**Figure 4: Impact of Syrian migration on the share of formally employed LTHS workers and wage distribution of native workers**




(a) (b)

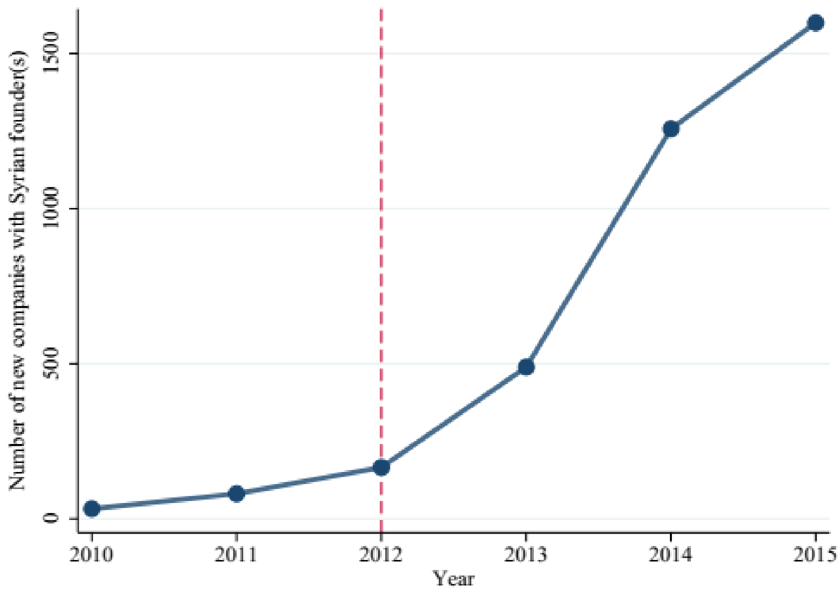
Notes: Panel (a) plots the change in the share of formally employed native LTHS workers in the treated regions compared to the counterfactual. Panel (b) plots the percentage point change in the share of workers earning above multiples of the national minimum wage in the treated regions compared to the counterfactual. The vertical dash line indicates the first year of the migration shock. The generalized synthetic control method (GSC) is employed in both graphs. The second x-axis in Panel (b) is the national-level average wage percentile value corresponding to the multiples of the national minimum wage. Both panels use the 2004-2015 NUTS-2-by-year aggregated TURKSTAT Household Labor Force Survey. The shaded area shows 95% confidence intervals for Panels (a) and (b) calculated using the parametric bootstrap of the GSC.

**Figure 5: Impact of the Syrian migration on the number of new dwelling unit building permits over time**

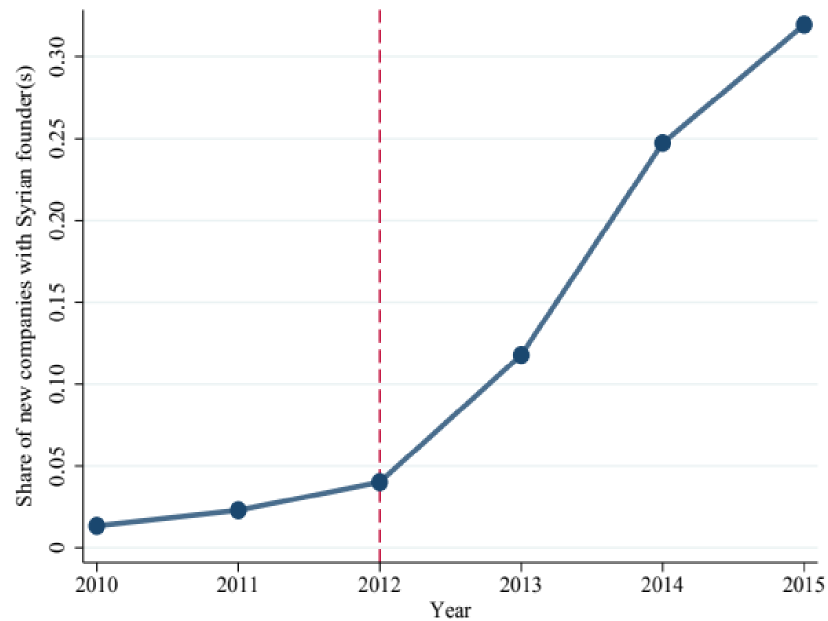



*Notes*: The figure plots the percentage change in the new dwelling unit building permits in the treated regions compared to the counterfactual, using the 2004-2015 province-by-year TURKSTAT Building Statistics. The vertical dash lines indicate the first year of the migration shock. The generalized synthetic control method is employed to estimate the impact. The shaded area shows the 95% confidence intervals, calculated using the parametric bootstrap of the GSC. For better precision, the regression is weighted by the pre-treatment gross provincial product.

**Figure 6: Number and share of companies with Syrian founders in Turkey**




(a)




(b)

*Notes*: Panel (a) plots the evolution of the number of firms founded by at least one Syrian cofounder. Panel (b) plots the share of firms founded by at least one Syrian cofounder out of all the firms founded by at least one non-native. The vertical dash lines indicate the first year of the migration shock.

# Appendix A: Data Appendix

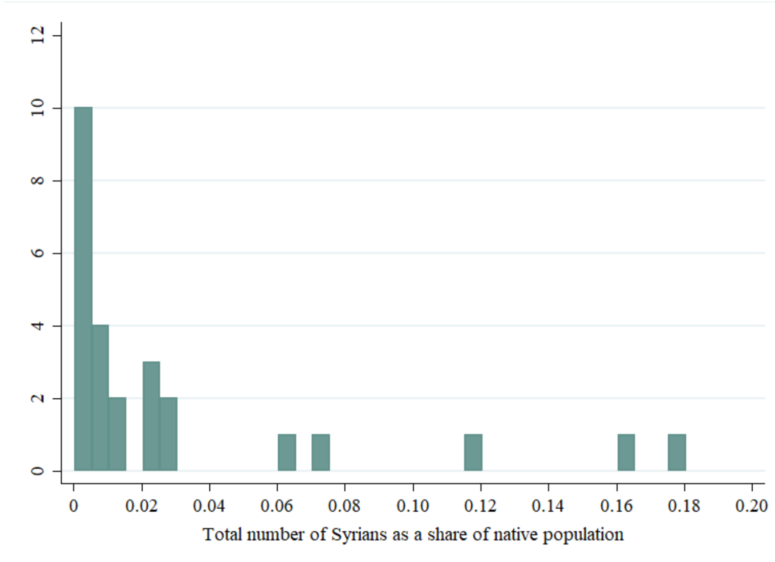
## Table A.1: Data Appendix

| Variables | Description | Panel Structure/Source |
|---|---|---|
| Total Number of Syrian Guests in Turkey | Total number of Syrian migrants temporary protection in Turkey | Annual, National-level / Ministry of Interior, Directorate General of Migration Management |
| Province-level residence data of Syrian guests in 2015 | Province level distribution of Syrians under temporary protection in 2015 | Province level / Ministry of Interior, Directorate General of Migration Management |
| Employment rate of Syrian guests | Employment rate of Syrian migrants at national level | National-level / Balcılar and Nugent (2016) |
| Treatment Regions (Provinces) | Regions (Provinces) that the number of Syrian migrants in 2015 is more than 10% of the native population are considered as treated regions. The first treatment year is 2012. Used in the DiD and the GSC. | Annual, NUTS-2 or province-level / Constructed variable |
| Control Regions (Provinces) | Regions (Provinces) that the number of Syrian migrants in 2015 is less than 2% of the native population are considered as control regions. Used in the DiD and the GSC. | Annual, NUTS-2 or province-level / Constructed variable |
| Native Population | The total number of native population. | Annual, province level / TURKSTAT |
| Native Working Age Population | The number of native population of ages 15-64. | Annual, NUTS-2 level / TURKSTAT Household Labor Force Survey |
| Employment | The number of native working population between ages 15-64. | Individual level / TURKSTAT Household Labor Force Survey |
| Informal Employment | The number of native working population between ages 15-64 with no social security coverage | Individual level / TURKSTAT Household Labor Force Survey |
| Age | The categorical age variable. Categories are [15, 20), [20, 25) . . . [60, 65). | Individual level / TURKSTAT Household Labor Force Survey |

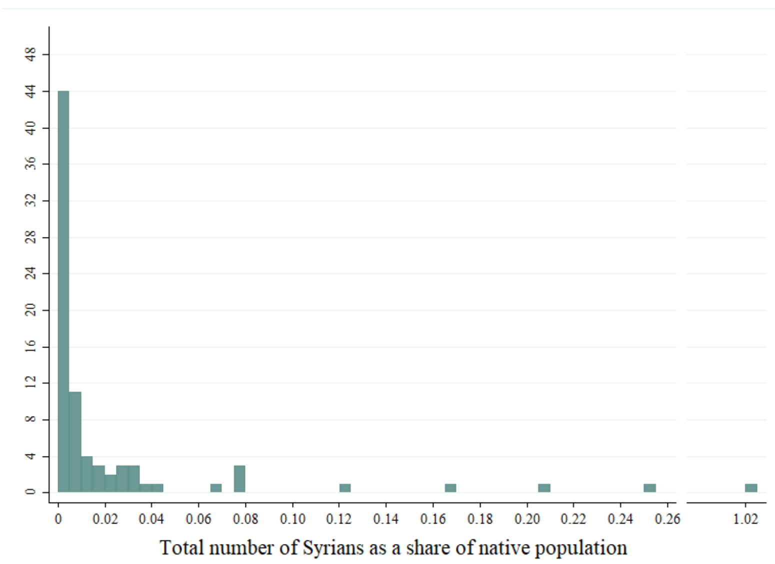
| | | |
|---|---|---|
| Education | The educational level of the native population between ages 15-64. Categories are; less than primary school, primary school, middle school, high school, vocational high school, some college or college, graduate school. | Individual level / TURKSTAT Household Labor Force Survey |
| Wage | Monthly after tax wage data of the native working population between ages 15-64. Includes bonuses, performance pays. | Individual level / TURKSTAT Household Labor Force Survey |
| New Residential Building Permits | The number of new building permits given for dwelling purposes. Administrative data. | Annual, Province level / TURKSTAT |
| New Residential Occupancy Permits | The number of new occupancy permits given for completed buildings for dwelling purposes. Administrative data. | Annual, Province level / TURKSTAT |
| Total number of new company establishments | The number of new company establishments in each province. Administrative data. | Annual, Province level / TOBB |
| Total number of firm establishments by Syrian founders, province-level | Similar to above, only by Syrian nationals. Administrative data. | Annual, Province level / TOBB, Özpınar et al. (2015) |
| Total amount of start-up capital invested | Total amount of capital invested initially in new firms. Administrative data. | Annual, Province level / TOBB |
| Total amount of start-up capital invested by Syrian founders | Similar to above, only by Syrian nationals. Administrative data. | Annual, Province level / TOBB |
| Gross Provincial Product | The value which is equal to the sum of the values of taxes minus subsidies and gross value added by province. | Annual, Province level / TURKSTAT |
| Arabic Speaking Population in 1965 | Total number of people with Arabic as the first language | Province level / TURKSTAT |
| Total number of public employees | Total number of public employees (4/c). | Province level / Social Security Administration |
| Total public services investment | Public investment in housing, education, health, and other public services. | Province level / Ministry of Development |

*Notes:* The table reports the variables, the descriptions, and the data sources used throughout the paper.

**Figure A.1: Frequency distribution of the Syrian migrants as a share of native population**




(a) NUTS-2 level




(b) Province level

Notes: The graphs plot the frequency distributions of the ratio of Syrian forced migrant population to the natives in 2015 at NUTS-2 (Panel (a)) and province level (Panel (b)). The x-axis shows the share, and the y-axis shows the number of NUTS-2 regions or provinces. The x-axis in Panel (b) is broken due to unusually large Syrian density in one province (Kilis). The data provided by Ministry of Interior Directory General of Migration Management is used.

# Appendix B: Additional Figures and Tables

This section presents additional figures and tables.

Figure B.1 shows the importance of purging the unobserved factors using the GSC method. In Panel A, we reproduce Figure 3 Panel B. The figure shows that prior to the migration shock, the counterfactual case and the actual case follow a similar path, suggesting the validity of the identifying parallel trends assumption.

In Figure B.1 Panel B, we use equation (1) without purging the confounding factors. This specification is similar in spirit to both of the traditional model specifications, as the border regions have the highest migrant to native ratios with a very large margin, and the border indicator is used as an instrument in the 2SLS model. We clearly see that the parallel trends assumption is violated prior to the migration. This suggests that the estimates obtained using the traditional model specifications are biased in examining the wage effects of the migration on the native LTHS workers, as the counterfactual case and the actual case follow different economic trends even before the migration wave.

There are certain differences in data collection methods between pre-2014 and 2014-2015 surveys. They are detailed in TURKSTAT (2014). In short, TURKSTAT started using the new administrative divisions. Some settlements that were previously considered as rural are united with greater municipalities, and they are no longer categorized as rural. More specifically, in 2013, the number of rural (urban) settlements was 36,854 (376) according to the pre-2014 divisions, and it was 19,078 (509) according to the 2014 divisions. Similarly, the nation-wide rural share of population in 2013 was 27.7% using the old administrative divisions, yet it was 13.5% according to 2014 regulations. As a result, the TURKSTAT removed the rural indicator variable from 2014 and 2015 surveys to prevent its misuse.

Although we do not employ urban-rural divisions in our analyses, one concern might be that these changes affect our estimates if the relative weights of observations in urban and rural settlements are substantially modified. For instance, if employment rates in rural areas are higher and the control regions are more rural than the treated, then there might appear a drop in average employment rate in control regions with the change in sampling methodology. To address this, we construct a control group that is similar to the treated group in terms of 2011 rural share of population. For this purpose, we remove 4 control regions that are substantially more rural than any of the treated regions, as the rural shares between treated and control regions are moderately different, 39.8% and 44.1%, in our main analyses. Excluding these regions decreases the rural share of the population in the control regions from 44.1% to 39%.

In Tables B.1 and B.2, we present the estimates of employment and wage effects with the control sample excluding the 4 most rural control regions. We employ the GSC model. All the estimates are essentially the same as the ones presented in the main text, indicating that the new administrative divisions have not affected our findings.

Table B.3 reports the employment effect of the Syrian migrants on certain sub-groups of the native LTHS population. The first column reports the change in teen employment-rate. The second and third columns examine LTHS men and women separately to assess whether the effects vary by gender. The fourth column reports the change in informally employed LTHS workers, the intersection of highly impacted group and highly impacted jobs. The last column excludes middle school graduates from the highly impacted group, and only considers individuals with less than middle school degree. We find a sizable or statistically significant negative effect for none of the sub-groups. The absolute magnitudes of the estimates are all smaller than 0.01. This suggests that the skill composition of the native LTHS workers has not changed as a result of the migration.

**The government expenditure in the treated regions**

The main reason behind the absence of an adverse effect might be that it is the government intervention that enabled the labor markets in the host regions to absorb the migrant labor force. To assess whether this explains the demand boost, we examine the percentage changes in the number of public employees and total public services investment after the Syrian migration using the 2SLS specification in Table B.4.[1] An increase in the outcomes might suggest a government intervention.

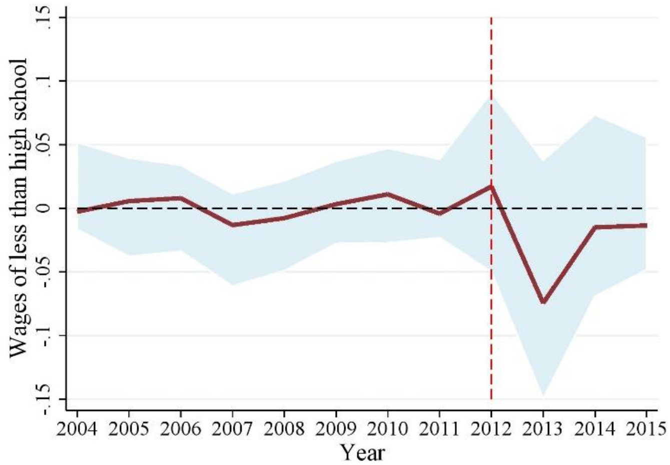
The first column indicates a slight decline of 1.5% in the number of public employees. The point estimate is statistically indistinguishable from zero and quite small. As we document in column (2), there is no statistically significant increase in the total public services investment in the treated regions either.

The results suggest that the government intervention is unlikely to explain the demand boost. We would like to emphasize that the findings do not imply that the Turkish government made no or little spending on Syrian migrants. Nevertheless, it is difficult to obtain a credible estimate for the size of the expenditure. The Turkish government has a motivation for overestimating the expenditure to get larger financial support from the European Union. For instance, in October 2015 the Turkish President Erdogan claimed that Turkey has made an expense of $8 billion for Syrian migrants in the country. However, Gürses notes that his investigation suggests a considerably smaller amount, only $1.8 billion over 2011 to 2015; hence the overwhelming portion of the claimed expense is unexplained (Gürses, 2015).

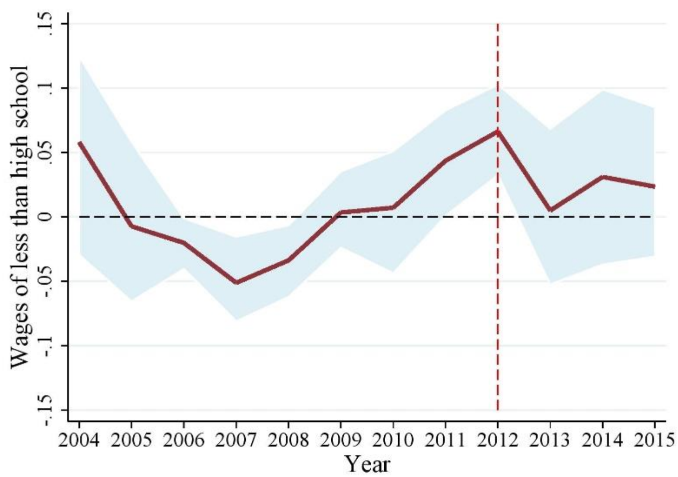
[1]We do not report the OLS model since it points towards the same results. The GSC is not feasible due to the short time window (2009-2015) in column 1. In column 2, the GSC recommends the use of the DiD.

**Figure B.1: Impact of the Syrian migrants on the native LTHS wages; alternative model specifications**

Panel A: GSC model (unobserved factors purged)




Panel B: Traditional Difference-in-Differences Model (unobserved factors not purged)




Notes: The graphs plot the evolution of the average native LTHS wage in the treated regions, using the 2004-2015 NUTS-2-by-year aggregated TURKSTAT Household Labor Force Survey. The vertical dash lines indicate the first year of the migration shock. Panel A uses the GSC model to purge the confounding factors, while the Panel B is the traditional difference-in-difference model described in the text. The dependent variables in both panels are the average (residual) log wage.

**Table B.1: Impact of Syrian migrants on native employment; excluding 4 most rural control regions**

| | (1) | (2) |
|---|---|---|
| $\hat{\beta}$ | -0.004 | 0.053 |
| SE | (0.034) | (0.049) |
| P-value | 0.867 | 0.366 |
| #Unobserved factors | 1 | 0 |
| # Clusters | 15 | 15 |
| # Treated clusters | 3 | 3 |
| Observations | 180 | 180 |
| **Groups:** | LTHS | HSG |

*Notes.* The table reports the change in the native LTHS and HSG employment rates in the treated regions after the migration shock, using the 2004-2015 NUTS-2-by-year aggregated TURKSTAT Household Labor Force Survey. In constructing the counterfactual, the 4 most rural regions are excluded from the primary control sample. The GSC model is employed. The standard errors clustered at NUTS-2 level are reported. The p-values are produced by the parametric bootstrap technique of the GSC.

**Table B.2: Impact of Syrian migrants on native wages; excluding 4 most rural control regions**

| | (1) | (2) |
|---|---|---|
| $\hat{\beta}$ | -0.006 | 0.045 |
| GSC SE | (0.037) | (0.026) |
| GSC p-value | 0.562 | 0.068 |
| #Unobserved factors | 2 | 2 |
| # Clusters | 15 | 15 |
| # Treated clusters | 3 | 3 |
| Observations | 180 | 180 |
| **Groups:** | LTHS | HSG |

*Notes.* The table reports the percentage change in the (residual) wages of the native LTHS and HSG workers in the treated regions after the migration shock, using the NUTS-2-by-year aggregated 2004-2015 TURKSTAT Household Labor Force Survey. In constructing the counterfactual, the 4 most rural regions are excluded from the primary control sample. The GSC model is employed. The standard errors clustered at NUTS-2 level are reported. The p-values are produced by the parametric bootstrap technique of the GSC.

**Table B.3: Impact of Syrian migrants on employment; additional findings from sub-groups**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\hat{\beta}$ | 0.007 | 0.000 | -0.001 | -0.002 | 0.001 |
| GSC SE | (0.053) | (0.044) | (0.025) | (0.043) | (0.052) |
| P-value | 0.717 | 0.949 | 0.965 | 0.920 | 0.999 |
| #Unobserved factors | 1 | 2 | 0 | 1 | 1 |
| # Clusters | 19 | 19 | 19 | 19 | 19 |
| # Treated clusters | 3 | 3 | 3 | 3 | 3 |
| Observations | 228 | 228 | 228 | 228 | 228 |
| **Groups:** | Teen | LTHS, man | LTHS, woman | LTHS, informal | Less than middle school |

*Notes.* The table reports the change in the native teen, LTHS male, LTHS woman, LTHS informal employment rates, and employment rate of native individuals with no middle school degree (LTMS) in the treated regions after the migration shock, using the 2004-2015 NUTS-2-by-year aggregated TURKSTAT Household Labor Force Survey. The dependent variables are the native teen, LTHS male, LTHS woman, LTHS informal, and LTMS employment counts normalized by 2011 population of the demographic group. The GSC model is employed. The standard errors clustered at NUTS-2 level are reported. The p-values are produced by the parametric bootstrap technique of the GSC.

**Table B.4: Impact of Syrian migration on the number of public employees and the public service investment**

| | (1) | (2) |
|---|---|---|
| % change | -0.015 | 0.011 |
| | (0.016) | (0.100) |
| P-value | 0.329 | 0.909 |
| # Clusters | 81 | 81 |
| Years | 2009-2015 | 2004-2015 |
| Observations | 567 | 972 |
| **Outcome:** | # Public employees | Public services investment |

*Notes.* The table reports the percentage changes in the number of public employees and in the public services investment in the treated regions after the migration shock. The standard errors are clustered at province level and the corresponding p-values are reported for inference.

## Appendix C: The Empirical Findings vs. The Canonical Model Predictions

In this section, we discuss the predictions of the canonical model and compare them with the empirical estimates we report in the main paper.

The canonical model in the immigration literature assumes that the economy is governed by a two-level constant elasticity of substitution production (CES) function where aggregate production, Q, primarily depends on the capital stock, K, and the number of laborers in efficiency unit, L. [1] In calculating L, another CES function is employed to homogenize different types of labor (H subscript for high-skilled and L for low-skilled workers). Therefore, the model can be written as follows:

$$Q = A * \left((1-\alpha)K^{\rho} + \alpha L^{\rho}\right)^{\frac{1}{\rho}}, \tag{C.1a}$$

$$L = \left(\theta L_L^{\eta} + (1-\theta)L_H^{\eta}\right)^{\frac{1}{\eta}}, \tag{C.1b}$$

where $\alpha$ and $\theta$ correspond to the distribution parameters between K and L, and $L_L$ and $L_H$. A is the residual (factor neutral technology coefficient). The elasticity of substitution between K and L is $\sigma_{KL} = \frac{1}{1-\rho}$, and that between $L_L$ and $L_H$ is $\sigma_{L_L L_H} = \frac{1}{1-\eta}$.

According to the canonical model, the Syrian migration shifts the labor supply of lower-skilled workers ($L_L$) and leaves all else constant in the short-run. In the long-run, the capital-labor ratio (and, thus, the average wage level) returns to its original level.

[1] See Borjas (2014) for more details.

After some algebraic manipulation, in the long-run, we obtain that changes in the wages of the lower-skilled workers is determined by the following formula:

$$dlnw_L = dlnw + (1 - \eta)(dlnL - dlnL_L). \qquad \text{(C.2)}$$

Therefore, the elasticity of substitution between lower- and higher-skilled labor, $\sigma_{L_L L_H}$, the changes in the amount of efficiency unit of labor, L, and the change in the number of lower-skilled laborers, $L_L$, are the only determinants of the lower-skilled workers' average wage change. In the following part, we will estimate each one of these terms.

**Elasticity of Substitution between Lower and Higher-Skilled Labor**

Following Katz and Murphy (1992), we employ the following model to estimate the elasticity of substitution between lower- and higher-skilled labor:

$$dln\left(\frac{w_{L_H}}{\mathrm{w_{L_L}}}\right) = \mathrm{dln}\left(\frac{1-\theta}{\theta}\right)_t - \frac{1}{\sigma_{L_L L_H}} * d\ln\left(\frac{L_H}{L_L}\right)_t. \qquad \text{(C.3)}$$

This formula, can be derived through algebraic manipulations of the CES model, suggests that, in the long-run, the change in the relative wages depends on two factors: the general trend (the first term), and the relative changes in the lower- and higher-skilled labor supply.

Using the data that belong to the pre-treatment periods (2004 to 2011), we estimate the following for Turkey:

$$\ln\left(\frac{w_{L_H}}{w_{L_L}}\right) = 0.031(0.004) * year - 0.679(0.155) * \ln\left(\frac{L_H}{L_L}\right).$$

In other words, there is a detectable skill biased technical change in Turkey for the years 2004-2011, and the elasticity of substitution between lower- and higher-skilled labor is 1.473. These estimates are similar to the ones commonly estimated in the literature (e.g. Card (2009)).

### Changes in the Number of Lower-Skilled Labor

To obtain $dlnL_L$, we calculate changes in the number of native as well as migrant lower-skilled labor. It is estimated that in 2015, approximately 400,000 Syrian forced migrants were employed in Turkey. Distributing this number to the regions in Turkey using the spatial distribution of the Syrian population, we estimate that more than 200,000 Syrian forced migrants were employed in the 3 NUTS-2 regions we defined as treated regions. Given the language barrier, the relatively low educational credentials, and the near impossibility of being formally employed, it is safe to assume that only a negligible share of the migrants can be categorized among higher-skilled workers.

Using the GSC estimates for the lower-skilled employment rate effects of the migration, we find that the number of native lower-skilled workers has increased by 3.5% between 2011 and 2015.[2] Combining the increase in the native and migrant lower-skilled workers, we calculate that $L_L$ has increased by 17.2%.

### Changes in the Amount of Efficiency Unit Labor

To estimate the percentage change of $L$, we simply plug the numbers we estimated into the equation (C.3).[3] Given that we calculate $L_L$ has increased by 17.2% and the elasticity of substitution between lower and higher-skilled labor is 1.473, the only missing term is the change in the number of higher-skilled workers. Using the GSC estimates, we obtain that the number of higher-skilled workers has

[2] The estimated percentage point change in the lower-skilled employment rate between 2011 and 2015 is 1.3%. Dividing this number by the 2011 employment rate in the treated regions yield 3.5%.
[3] We remain agnostic about the distribution parameter and assume that $\theta = 0.5$.

increased by 5.1% between 2011 and 2015. Therefore, the amount of efficiency unit labor has increased by 12.7%.

**The Canonical Model Predictions for the Native Lower-Skilled Wage Change and the Empirical Results**

Using the percentage changes in $L$ and $L_L$, we calculate that the canonical model that assumes no native-migrant complementarity, and that considers the migration merely as a labor supply shock, predicts that wages of the native lower-skilled workers would decline by 4.0% between 2011 and 2015 due to the Syrian migration. Note that this number is obtained for the long-run; i.e. assuming that the capital is fully adjusted. Nonetheless, the empirical point estimate for the change between 2011 and 2015 is only -0.9%. This is less than a fourth of the canonical model estimate. This implies that the canonical model omits certain important demand channels that counteract the potential adverse effects of the migration.