Refugees, Amenities, and the Skill Premium*

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Abstract

This paper examines how intra-national native migration patterns and region-specific welfare respond to large inflows of immigrants. Leveraging the case of Turkiye, which experienced a substantial influx of Syrian refugees following the 2011 Syrian Civil War, I first provide reduced-form evidence on the effects of the influx on local labor markets and housing rents across skill groups. I then document an increase in native outmigration from refugee-concentrated areas, particularly among the high-skilled, alongside a significant deterioration in local amenities. These changes disproportionately burden the low-skilled natives, deepening pre-existing disparities between skill groups. Finally, to quantify the role of amenity changes in shaping native outmigration, I develop a dynamic spatial general equilibrium model in which amenities evolve endogenously and affect natives' migration decisions through estimated, skill-specific amenity taste parameters. The model highlights amenity deterioration as a key mechanism behind native flight, and shows how differential mobility and amenity preferences reinforce rising skill premiums. It also provides a basis for counterfactual experiments that explore the effects of refugee reallocation policies and targeted subsidies. These demonstrate the potential for policy interventions to reduce regional distributional gaps and welfare losses.

Keywords: Spatial Dynamics, Migration, Amenities, Skill Premium, Labor Markets

JEL Codes: J31, J61, O15, R23

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1 Introduction

Global refugee flows have surged over the past decade, with an estimated 1.2% of the world's population now forcibly displaced. These large population movements pose complex economic challenges for host countries, influencing labor market dynamics, housing availability, and patterns of internal migration. While much of the existing literature has focused on wage and employment effects, a growing concern is the strain such inflows place on local amenities, which may deteriorate as a result of increased demand and limited fiscal capacity. In this context, native migration responses are shaped not only by labor market competition but also by changes in the quality of place-based amenities. Importantly, these responses are heterogeneous, as relocation patterns differ across skill groups, with high- and low-skilled natives facing distinct trade-offs in the presence of refugee inflows. Understanding how refugee inflows affect both local amenity provision and skill-specific migration decisions is therefore critical for evaluating the broader spatial and economic impacts of forced migration.

This paper examines the case of Turkiye, which experienced a large and rapid influx of Syrian refugees following the 2011 Syrian Civil War. Under an open-door policy, refugee numbers rose from roughly 10,000 in 2011 to 2.5 million by 2016 and nearly 4 million by 2021, with most settling in southeastern border provinces. As refugees arrived, high-skilled natives disproportionately migrated out of these regions, coinciding with a rising skill premium in those regions that they left. I document these patterns using administrative data from Turkish Statistical Institute (TurkStat) and examine the effects of the influx on local labor markets, housing rents, and native mobility. A central question becomes: What drives natives to avoid immigrant-concentrated areas? Understanding the drivers of high-skilled outmigration is crucial, as I will later provide evidence that this outmigration causes rising skill premiums and, in turn, growing inequality between different skill groups. Identifying the mechanisms behind native avoidance of refugee-concentrated areas would inform policy efforts to mitigate these disparities and promote more equitable regional outcomes of wages, rents, and amenities in Turkiye.

The Syrian refugee influx began in 2011 with Turkiye's open-door policy, which was later institutionalized through the temporary protection policy granting access to healthcare, education, and legal employment. At its peak, Turkiye hosted nearly 4 million Syrians, more than any other country. Most initially settled in southeastern provinces such as Sanliurfa, Gaziantep, Hatay, Kilis, and Mardin, where the government concentrated refugee camps and infrastructure. This pattern was not driven by formal mobility restrictions but by the economic infeasibility of moving to more distant provinces. While the immigrant mobility expanded over time, early settlement patterns shaped geographic concentration for years. These border regions became the frontline of the humanitarian response, facing substantial pressure on services, housing, and labor markets. Refugees, largely low-skilled, entered sectors like agriculture, construction, and textiles, often with limited legal protections.

Although Turkiye's policy approach was initially praised, rising social tensions and economic pressures have fueled public debate over repatriation. Despite government programs to encourage return, most refugees remain due to safety risks in Syria, and the Southeast continues to be a focal point of humanitarian and policy challenges. The counterfactual policy evaluations in this paper, along with those I propose for future work, aim to address these challenges.

My paper builds most directly on the labor market literature, while also contributing new evidence on amenities. A large and growing body of research has examined the economic consequences of refugee inflows across a range of outcomes, with one strand focusing specifically on labor market impacts, including Card (1990), Ruiz and Vargas-Silva (2015), Del Carpio and Wagner (2015), Akgündüz et al. (2015), Stave and Hillesund (2015), Ceritoglu et al. (2017), Borjas and Monras (2017), Clemens and Hunt (2017), and Peri and Yasenov (2019). Another strand highlights the impacts on general prices, as in Alix-Garcia and Saah (2009), Tumen (2016), Balkan and Tumen (2016), Al-Hawarin et al. (2018), and Balkan et al. (2018). Additional work points to effects on firms by Akgündüz et al. (2018) and Altındağ et al. (2020). There are also studies by Tumen (2018), and Rozo and Vargas (2020) focusing on education, as well as Ibanez et al. (2021) on health. In this paper, I construct an amenity index that encompasses not only education and health, but also environment, crime, and culture.

The housing market plays a central role in this paper, as existing housing supply constraints in Turkiye shape how regions adjust to refugee inflows. This is consistent with its broader importance as a key margin of adjustment in the migration literature. Saiz (2003) and Saiz (2007) show that immigration can raise local rents, an effect that persists even when natives are mobile Saiz and Wachter (2011). Other studies emphasize house quality heterogeneity Depetris-Chauvin and Santos (2018), Lastrapes and Lebesmuehlbacher (2020), which I account for empirically in my study. Housing supply constraints, highlighted by Gonzalez and Ortega (2013), are especially relevant for Turkiye, and Rozo and Sviatschi (2021) show that inelastic housing supply amplifies rent increases in refugee-hosting areas. I extend this literature by incorporating amenity deterioration alongside housing supply constraints, where the two jointly determine native migration responses.

My paper examines how refugee immigration affects native mobility and wages across different skill groups. In analyzing native mobility, it relates to studies such as Card (2001), Peri and Sparber (2011), Mocetti and Porello (2010), and Wozniak and Murray (2012). Regarding wage disparities, it connects to work by Bakens et al. (2012), and Ottaviano and Peri (2006). A further strand of the literature distinguishes impacts by native skill level, including Borjas (2003), Manacorda et al. (2012), Ottaviano and Peri (2012), and Caiumi and Peri (2024). While my paper aligns with this line of work by differentiating households by skill, it departs from prior studies that largely highlight complementarities between natives and immigrants. Much of this literature finds that immigration can generate positive outcomes when skill differences between groups are large. In contrast, the refugee inflow to Turkiye was predominantly low-skilled and concentrated in regions already populated by low-skilled natives, making this composition central to wage divergence between native skill groups.

Regional amenities constitute a central component of this paper's framework, as I model their evolution over time as a determinant of natives' reallocation decisions. Prior work, such as Roback (1982), shows that local wage differentials are largely explained by amenities, and Accetturo et al. (2014) demonstrate that amenities, even when treated as exogenous, shape location choices. Building on this, Diamond (2016) incorporates amenities into household utility and allows them to evolve endogenously with the skill composition of residents, thereby influencing location preferences across groups. Related studies such as Bayer et al. (2004), Bayer et al. (2007), Card et al. (2008), and Guerrieri et al. (2013) examine how regional amenities change in response to resident composition. The novelty of my paper is to allow for endogenous amenity evolution within a spatial general equilibrium framework, where amenity taste parameters differ by household type, capturing heterogeneous amenity preferences. This framework enables me to quantify how refugee-induced changes in amenities and labor markets jointly shape natives' dynamic migration decisions. Heterogeneous preferences for amenities in spatial equilibrium have also been discussed in Roback (1988) and Beeson (1991), though these studies do not estimate amenity preferences directly.

This paper introduces a novel dimension by examining all these effects discussed within a dynamic framework, where households make intertemporal migration decisions based on anticipated changes in wages, rents, and amenities. For the structural analysis, I develop a dynamic spatial general equilibrium model with regionally distinct labor markets. Households make forward-looking migration choices, following the framework of Caliendo et al. (2019), and I model skill-specific mobility patterns in line with Caliendo et al. (2023). As an extension to my baseline model, I incorporate a subsidy channel where amenities respond not only to the existing population but also to government transfers to regions, one source being increased tax revenues. Relatedly, Fajgelbaum et al. (2018) examine how state taxes shape worker allocation in a spatial general equilibrium, though their model does not incorporate amenities. In my framework, amenities become the intermediate channel, as they are affected by taxes and in turn influence relocation decisions. My model also enables counterfactual exercises, such as refugee reallocation and targeted subsidies, to assess their potential to mitigate regional disparities and shifts in economic outcomes.

Lastly, my work contributes to the literature by providing a new case study on the impact of a refugee influx in Turkiye, complementing studies that examine the labor market effects of low-skilled immigration to the United States as in Peri (2011), Monras (2020), Lee et al. (2022); and to the Europe as studied by Edo and Özgüzel (2023), Dustmann et al. (2016), and Hatton and Tani (2005). Although my structural model differs in important ways, it is most comparable to Kim et al. (2022), which analyzes the South Korean case where amenity dynamics in response to immigration are also central. However, both the model and the context differ substantially. Kim et al. (2022) employs a model of optimal location choice based on the Multinomial Logit framework of McFadden (1973), whereas I use a dynamic spatial general equilibrium model following Caliendo et al. (2019). Contextually, South Korea's population is largely high-skilled, so the arrival of low-skilled immigrants, while deteriorating amenities, raises native wages due to complementarities across skill groups. By contrast, the Southeast of Turkiye is predominantly low-skilled, so the economic and distributional impacts diverge considerably.

The rest of the paper is organized as follows. Section 2 provides background on the Syrian migrants. Section 3 presents empirical evidence on Turkish natives' responses to the refugee influx. Section 4 introduces the structural model, Section 5 describes the estimation strategy, and Section 6 reports the baseline results together with counterfactual analyses. Section 7 outlines an extension of the baseline model in which a tax revenue channel affects amenity evolution and presents its results and counterfactuals. Section 8 focuses on household utility changes, interregional comparisons beyond the Southeast, and alternative substitution parameters between low-skilled natives and refugees to assess robustness and provide comparative analysis. Section 9 concludes, and Section 10 discusses further potential extensions of this paper for future research.

2 The Migrants

In this section, I begin by documenting the spatial and temporal distribution of Syrian refugees. Then using individual-level microdata, I summarize the demographic characteristics of the migrants. Figure 1 below presents the cumulative number of Syrian refugees in Turkiye using data from the refugee survey by AFAD[1]. The red line represents the number of refugees residing in the Southeast region, while the green line represents the total number for all of Turkiye. The figures, expressed in millions, reveal that approximately two-thirds of the Syrian refugee population has settled in the Southeast. In terms of refugee shares relative to the total population, by 2016, refugees accounted for 3% of Turkiye's total population and 11% of the Southeast.[2] The Southeast region, shaded in dark blue on the map in Figure 2, is the area most affected by the refugee influx.

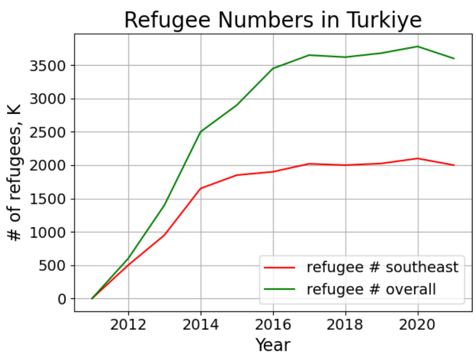

Figure 1: Influx of Syrian Refugees

(AFAD Survey Data)

Figure 2: Map of Turkiye

According to the AFAD survey data, 91.6% of Syrian refugees had a high school degree or below, and only 8.4% held a university degree or higher. Due to this distribution of educational attainment, together with the existing language barriers, as Syrians speak Arabic rather than Turkish, I classify

[1] AFAD: Disaster and Emergency Management Authority of Turkiye

[2] Especially after 2014, movement toward western cities increased as refugees sought better employment opportunities and public services while local economies in the southeast started becoming saturated.

all refugees as low-skilled later in my model for analytical simplicity. Finally, it is important to note that, under Turkiye's temporary protection policy, refugees are permitted to obtain work authorization, therefore can enter the formal labor force as natives. However, an important distinction is that refugees face significantly higher internal migration costs within Turkiye once they enter the country. Therefore, as discussed in more detail in Section 4, my model assumes infinite migration costs for Syrians within Turkiye. Figure 3 displays the evolution of refugee presence across the Southeast, motivating the increased refugee intake in Turkiye across years following the Syrian Civil War.

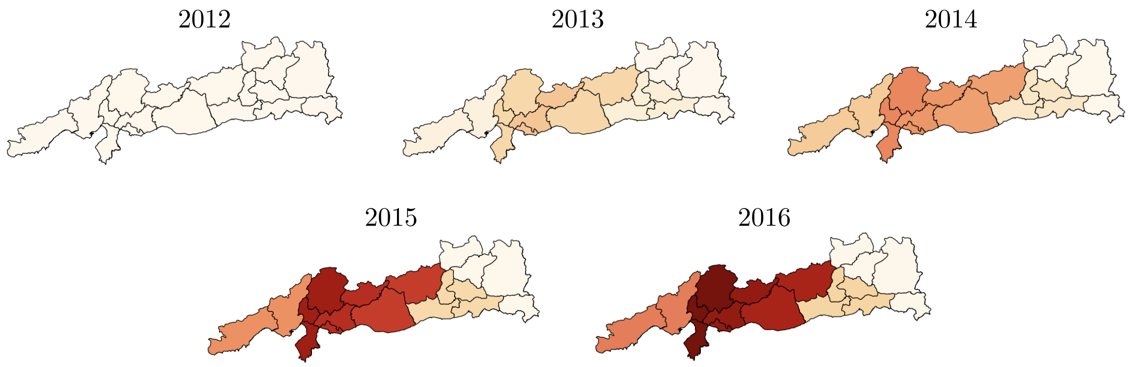

Figure 3: Refugee Intake in the Southeast, Province Level

(AFAD Survey Data)

Table 1 provides a breakdown of refugee educational attainment, confirming that a small minority hold tertiary degrees. Table 2 shows upward income mobility over time for the refugees, with a shift from lower to higher income brackets over time. Annualizing these figures, refugees earned approximately 3,000 USD in 2013, which was substantially lower than low-skilled natives. But they earned nearly 4,500 USD by 2017, which is comparable to the earnings of low-skilled natives in that same year, without controlling for tenure. Table 3 highlights the refugee population's age and dependency structure. We see that only 17.2% were heads of household, suggesting a relatively small active labor force share within the refugee population.

Educational Status	Number of People
Illiterate	1863
Literate	894
Primary School	4203
Secondary School	2671
High School	1382
Higher Education	1054

Table 1: Educational Status of Syrian Refugees in 2013 (AFAD Survey Data)

Monthly Income (USD)	% in 2013	% in 2017
≤ 249	56.0	32.1
250 - 499	40.5	50.4
500 - 999	2.9	15.4
$\geq 1,000$	0.6	2.1

Table 2: Monthly Incomes of Syrian Refugees (AFAD Survey Data)

Degree of Relationship	% of People
Head of the family	17.2
Spouse	15.0
Children	53.5
Children in law	1.7
Grand children	3.3
Other relatives	9.2

Table 3: Degree of Relationship to Household Head in 2013 (AFAD Survey Data)

3 Patterns of Turkish Responses

3.1 Effect of Refugee Influx on Annual Incomes

For the empirical analysis, I use an Income and Living Conditions Survey from the Turkish Statistical Institute (TurkStat), which is a representative repeated cross-sectional dataset spanning from 2006 to 2019. The data provide rich individual-level information, including demographic characteristics such as age, gender, education level; economic indicators such as occupation, monthly income, ability to make ends meet; and housing conditions such as rents, dwelling size, number of rooms, heating systems, and issues such as insulation or leakage problems. To capture refugee exposure across space and time, I construct the following variable, where r refers to the NUTS-2 regions[3], of which there are 26 in total.

$$syrian\_share_{rt} = \frac{\text{total number of refugees in region } r \text{ at time } t}{\text{total population of region } r \text{ at time } t}$$

I measure the effects of the refugee influx on natives' annual incomes by estimating the following specification, where the unit of observation is a household i in region r at time t, and H_{irt} denotes household-level controls:

$$ln\_income_{irt} = \beta_0 + \beta_1 syrian\_share_{rt} + \beta_2 H_{irt} + \lambda_t + \nu_r + \varepsilon_{rt}$$

Table 4 presents the coefficients for the variable $syrian\_share_{rt}$, controlling for $H_{irt} = \{age_{irt}, age\_squared_{irt}, household\_size_{irt}\}$[4], where age refers to the age of the household head. The first column reports the estimates for low-skilled natives and the second for high-skilled natives. The coefficient on the Syrian share variable is negative and statistically significant for low-skilled workers, indicating that an increase in the local refugee share is associated with a decline in their income. For high-skilled workers, the estimated coefficient is smaller in magnitude and statistically insignificant. These findings suggest that the refugee influx has had an adverse impact on the earnings of low-skilled natives, consistent with the findings of Card (2001) as well as theoretical expectations of increased competition in lower-wage labor markets.

	low-skill income	high-skill income
syrian share	-0.008***	-0.003
	(0.002)	(0.003)
Observations	86,296	18,872
R^2	0.135	0.186

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of Influx on Annual Incomes

[3]NUTS: Nomenclature of Territorial Units for Statistics

[4]Full tables for incomes, rents, migration, and amenities are provided in Appendix A.

This result is also displayed in the plot below, with a slight modification in the regression specification, where the variable of interest becomes $syrian\_share_{rt} \times \mathbb{1}_{\{year=t\}}$. Therefore, the plot presents a coefficient for each year both pre- and post-policy date of 2011, in order to display the trend across time.

$$ln\_income_{irt} = \beta_0 + \beta_{1,t}(syrian\_share_{rt} \times \mathbb{1}_{\{year=t\}}) + \beta_2 H_{irt} + \lambda_t + \nu_r + \varepsilon_{rt}$$

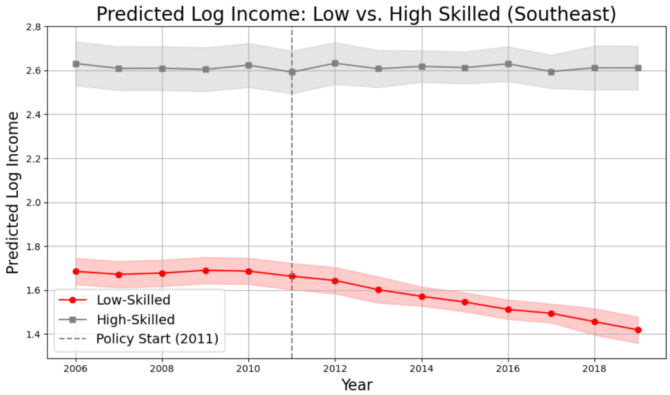

Figure 4: Income Plot

3.2 Effect of Refugee Influx on Rents in the Southeast

As the number of refugees in Turkiye increases, particularly in the Southeast, the rent gap between the Southeast and the rest of the country narrows considerably[5]. The left panel of Figure 5 shows that average rent in the Southeast, initially about 40% lower than the average in the rest of the country, converges to within 10% by 2016. This trend indicates that refugee-induced population growth exerted upward pressure on rents in the Southeast due to the increased demand for housing. Meanwhile, total housing supply remains relatively stable across regions, as shown in the right panel of Figure 5, suggesting that supply did not adjust to meet the surge in demand.

To measure the causal effect of the refugee influx on rents, I estimate the following equation, where the unit of observation is household i, in region r, at time t. The vector H_{irt} includes household-level controls, and X_{rt} captures region-level characteristics.

$$ln\_annualrent_{irt} = \beta_0 + \beta_1 syrian\_share_{rt} + \beta_2 H_{irt} + \beta_3 X_{rt} + \lambda_t + \nu_r + \varepsilon_{rt}$$

[5]Rent data are obtained from TurkStat and expressed in real terms after adjusting for inflation.

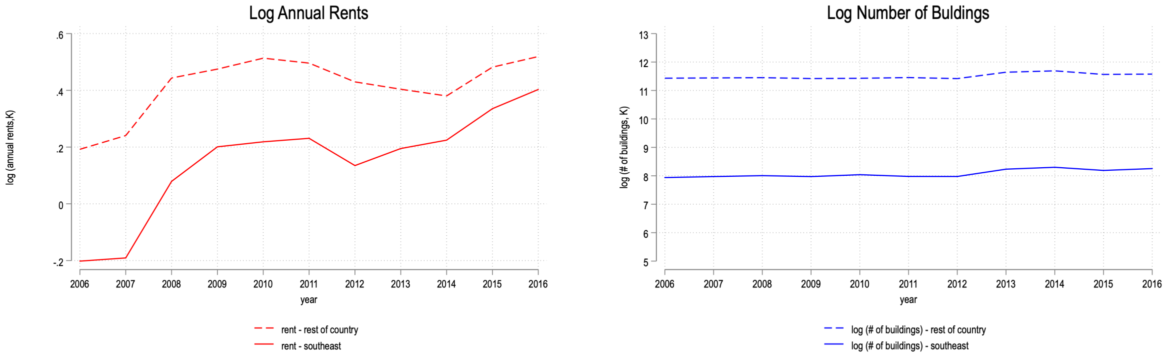

Figure 5: Housing Rents & Housing Supply

The analysis is conducted separately for high-skilled and low-skilled native households and further distinguishes between renters and owners (for whom the dataset provides imputed rental values[6]). Table 5 reports the coefficients for the $syrian\_share_{rt}$ variable for the low-skilled households in the first two, and for the high-skilled households in the latter two columns. Here, I control for $H_{irt} = \{house\_quality_{irt}, income_{irt}\}$, as well as $X_{rt} = \{health\_services_{rt}, no\_pollution_{rt}, no\_crime_{rt}\}$. The effects of the refugee influx are the most substantial for the low-skilled. This is consistent with the idea that refugees primarily affect segments of the housing market occupied by low-skilled natives. Here, only the coefficient of interest is displayed and the control variables used in the regression are suppressed for brevity. However, the full tables with all control variables as well as with different specifications for robustness are presented separately for each skill type in Appendix A.

	ls owner	ls tenant	hs owner	hs tenant
syrian share	0.008***	0.011***	0.001	0.020**
	(0.001)	(0.003)	(0.008)	(0.010)
Observations	88,606	37,120	15,364	11,923
R^2	0.436	0.385	0.389	0.470

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of Influx on House Rents

The results in Table 5 show that an increase in refugee share is associated with statistically significant increases in both owned and rented housing costs for low-skilled households. We also observe an increase for the high-skilled, however there is no significance for the owned houses and a smaller

[6] Imputed rents for owner-occupied housing are estimated by TurkStat based on nearby rental units of similar quality.

significance for the tenant occupied houses. The consistent significance of the coefficients indicates that increased refugee exposure drives up housing costs, particularly in the market segments occupied by low-skilled natives. The $house\_quality_{irt}$ variable, which used as a control variable within H_{irt}, is constructed via principal component analysis (PCA) based on a set of housing characteristics[7]. I use PCA to construct the amenity index as well, which I describe later in this section, as it plays a central role in the paper.

Similar to the analysis carried out for incomes, I conduct the analysis with time-specific coefficients for $syrian\_share$, here as well. In the plot below, we observe the predicted rents for low- versus high-skilled, where the variable of interest is $syrian\_share_{rt} \times \mathbb{1}_{\{year=t\}}$. In this plot, I gather all high-skilled into one group and all low-skilled into another, therefore the distinction of whether they reside in a rented or an owned house is removed in the plot. Even though both skill types face an increase in their house rents, we observe a much sharper rise in the low-skilled occupied house rents post-2011.

$$ln\_annualrent_{irt} = \beta_0 + \beta_{1,t}(syrian\_share_{rt} \times \mathbb{1}_{\{year=t\}}) + \beta_2 H_{irt} + \beta_3 X_{rt} + \lambda_t + \nu_r + \varepsilon_{rt}$$

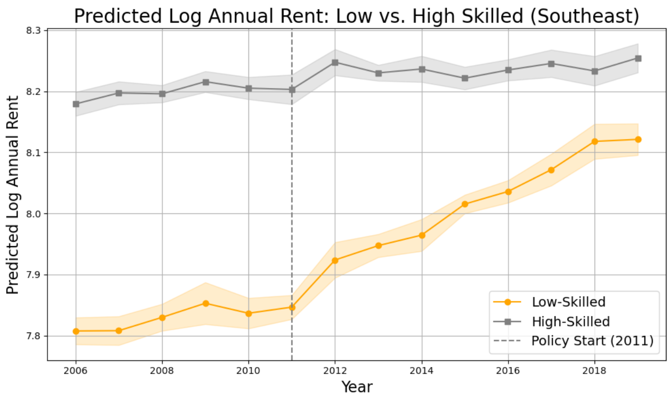

Figure 6: Rent Plot

3.3 Effect of Refugee Influx on High-Skilled Migration from the Southeast

This subsection presents causal evidence on the out-migration of high-skilled Turkish citizens from areas with high concentrations of refugees, commonly referred to as native flight. The following regression specification is estimated, where the unit of observation is city c and year t. I use the NUTS-3

[7]number of rooms available (kitchen, bathroom, toilet excluded); size in squaremeters; availability of heating system and type of fuel used; existence of bath/shower, indoor flushing toilet, kitchen, piped water system, hot water; problem of leaking roof, damp walls, rot in window frames, insulation, darkness

classification, corresponding to provinces, in contrast to earlier sections that relied on the NUTS-2 regional divisions (aggregates of cities).

$$ln\_flow_{ct} = \beta_0 + \beta_1 syrian\_share_{ct} + \beta_2 X_{ct} + \lambda_t + \nu_c + \varepsilon_{ct}$$

In Table 6, the first two columns report coefficients for $syrian\_share_{ct}$ for low-skilled inflows and outflows, respectively. Similarly, the latter two columns report results for high-skilled inflows and outflows. I control for $X_{ct} = \{income_{ct}, house\_quality_{ct}, education_{ct}, health\_services_{ct}\}$. Note that the variables of $income$ and $house\_quality$ are now city-time specific as the dependent variable of ln_flow is also city-time specific[8], unlike the dependent variable of $ln\_annualrent$ in the previous section which was household-region-time specific. I find a positive and statistically significant coefficient on the refugee share variable only for the high-skilled outflows, suggesting that greater refugee exposure is associated with increased out-migration of high-skilled natives. In contrast, the low-skilled outflows as well as the inflows of either type do not show statistically significant patterns. These results are robust to different specifications as shown in Appendix A.

	ls inflow	ls outflow	hs inflow	hs outflow
syrian share	-0.004	0.002	0.636	1.040***
	(0.003)	(0.003)	(1.050)	(0.362)
Observations	121	121	137	137
R^2	0.956	0.932	0.378	0.663

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect of Influx on Migration Flows of High-Skilled

Below, following the structure I utilized describing the empirical findings for income and rents, I continue with conducting the same analysis this time with time-specific coefficients for $syrian\_share$. In the plot below, we observe the predicted outmigration for high-skilled natives, where the variable of interest is $syrian\_share_{rt} \times \mathbb{1}_{\{year=t\}}$. I only display the plot for the inflow and the outflow for the high-skilled type. The inflow remains flat, whereas the outflow increases following the policy implementation, consistent with Table 6.

[8] Income and house quality are averaged at the city-time level separately for each skill group, rather than being measured at the individual level.

$$ln\_flow_{ct} = \beta_0 + \beta_{1,t}(syrian\_share_{ct} \times \mathbb{1}_{\{year=t\}}) + \beta_2 H_{ct} + \beta_3 X_{ct} + \lambda_t + \nu_c + \varepsilon_{ct}$$

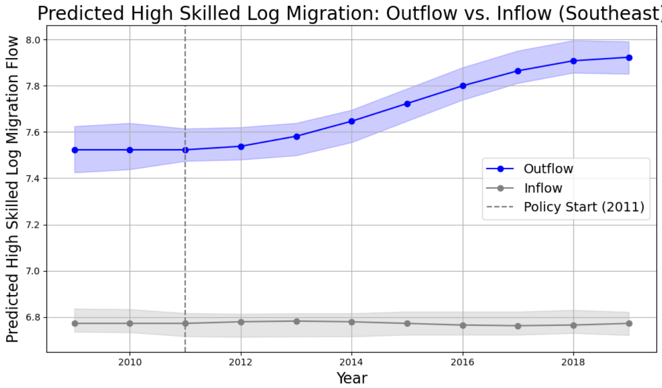

Figure 7: Migration Plot

3.4 Principal Component Analysis (PCA) for Amenities

Before presenting the reduced-form analysis of how the refugee influx affected local amenities, I describe how I construct regional amenity indices, which will serve as the dependent variable in the subsequent analysis. Using the survey data, I compile indicators for five distinct categories of local amenities, which are health, education, security, environment, and culture. These categories encompass a broad set of non-tradable public goods available in each region at each point in time, all being normalized by local population. I aggregate these indicators into a single amenity index using Principal Component Analysis (PCA), a standard method for dimensionality reduction that extracts the most informative linear combinations of the original variables.

Figure 8 presents the component loadings and Figure 9 presents the proportion of variance explained by each principal component. The heatmap shows that the first principal component is primarily driven by education, followed by security, environment, culture, and health, in descending order of influence. The second component, by contrast, is driven primarily by variation in health-related variables.

I retain the first two principal components, which together account for the majority of the variance across the five amenity categories. Specifically, the first component explains 69.3% of the total variation, and the second explains an additional 23.5%. These two components form the basis for my composite amenity index used in the subsequent empirical analysis.

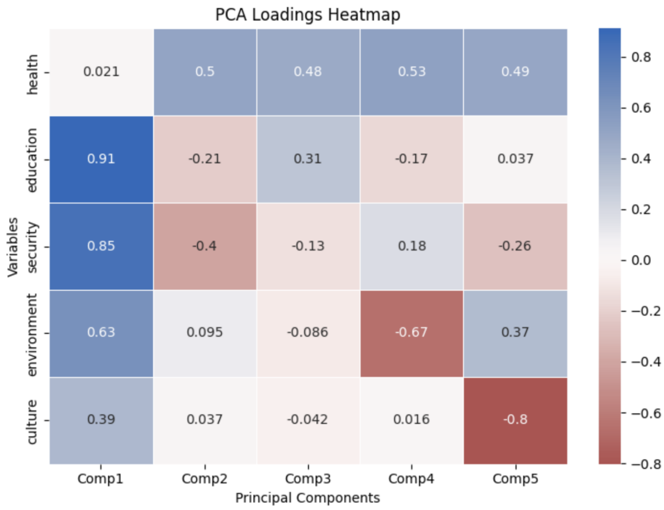

Figure 8: PCA Loadings Heatmap

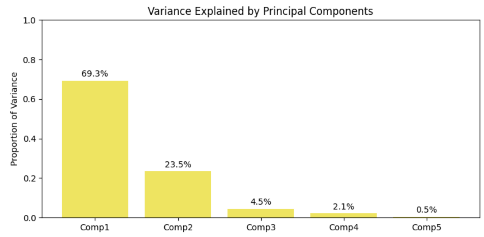

Figure 9: Component Variances

3.5 Effect of Refugee Influx on Amenities

After constructing the amenity index, I now examine the effect of the refugee influx on regional amenities. I use the amenity index as the dependent variable and Syrian refugee number as the main explanatory variable. However, a key endogeneity concern arises in this context. The refugees might systematically be selecting into regions with initially worse amenities due to those regions being more affordable. Also, they neither have enough knowledge nor easy access to these publicly provided goods before coming in to Turkiye. Therefore, this could cause a bias for the estimates of the effect of refugee inflows on amenity outcomes due to reverse causality.

To address this concern, I construct an instrumental variable for refugee exposure. Letting r denote the Turkish region as in previous subsections, the instrument combines the geographical distance from the Syrian border (T_r) and the initial distribution of refugees across Turkish regions following the first influx in 2011 (π_{r0}), scaled by the total number of refugees in Turkiye at time t (S_t). Here, it is important to note that Turkiye did not have a preexisting Syrian population, unlike for instance the United States in David Card's Mariel Boatlift study, where the incoming migrants joined an existing Hispanic community. Therefore, I use π_{r0} to capture the initial influx of Syrians at the onset of the Syrian Civil War. This variation is plausibly exogenous, as initial placements were determined by the Turkish government through a limited set of refugee camp locations rather than being chosen based on migrants' preferences. The instrument used for the number of refugees in region r at time t is then defined as:

$$S_{rt} = \left(\frac{1}{T_r}\right)^{\beta_1} (\pi_{r0} S_t)^{\beta_2}$$

Here, S_{rt} represents the predicted number of Syrians in region r at time t. Intuitively, this variable captures the idea that refugee inflows are more likely to be concentrated in regions closer to the Syrian border and those that had a larger initial share of refugees. Since the instrument depends only on geography and initial settlement patterns, it satisfies the exclusion restriction by being unrelated to current amenities, while remaining correlated with actual refugee shares. The idea behind π_0 being exogenous is that the government determined the initial locations of refugee camps, so refugees' own location preferences did not influence where they first settled. However, π_0 affects later settlements, as newly arriving refugees in subsequent years tend to locate near already-settled Syrians.

I estimate a two-stage least squares (2SLS) model. In the first stage, I regress the log of actual refugee numbers in a region on the log of inverse distance to the border and the log of the inital refugee share scaled by the total number of refugee population: $ln(S_{rt}) = \beta_0 + \beta_1 ln\left(\frac{1}{T_r}\right) + \beta_2 ln(\pi_{r0} S_t)$. In the second stage, I use the predicted refugee share $\hat{S}_{rt}$ to estimate the effect on the log of the regional amenity index: $ln(b_{rt}) = \alpha_0 + \alpha_1 ln(\hat{S}_{rt}) + \lambda_t + \nu_d$

$$ln(\hat{S}_{rt}) = \hat{\beta}_0 + \hat{\beta}_1 ln\left(\frac{1}{T_r}\right) + \hat{\beta}_2 ln(\pi_{r0} S_t) + \lambda_t + \nu_d$$

	ln_syrian_num
ln_dist_inv	0.081**
	(0.035)
ln_fracxsyrian_tot	0.952***
	(0.011)
Observations	442
R^2	0.998

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Stage 1

$$ln(b_{rt}) = \alpha_0 + \alpha_1 ln(\hat{S}_{rt}) + \lambda_t + \nu_d$$

	ln_amenity_endo_idx
ln_syrian_num_hat	-0.025***
	(0.006)
Observations	312
R^2	0.949

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Stage 2

The results from both stages are presented in Tables 7 and 8. The first-stage estimates confirm that refugee distribution is strongly predicted by distance to the border and the initial settlement pattern. In the second stage, I find a statistically significant negative effect of refugee exposure on regional amenities. This suggests that refugee inflows are associated with a deterioration in non-tradable public goods, i.e. amenities.

Finally, below, I again follow the structure I used for the three empirical findings I presented earlier, this time for amenities. In the plot below, we observe the predicted amenity index deteriorating over time post-policy, where the variable of interest is $syrian\_share_{rt} \times \mathbb{1}_{\{year=t\}}$.

$$ln(b_{rt}) = \alpha_0 + \alpha_{1,t}(\hat{S}_{rt} \times \mathbb{1}_{\{year=t\}}) + \lambda_t + \nu_r + \varepsilon_{rt}$$

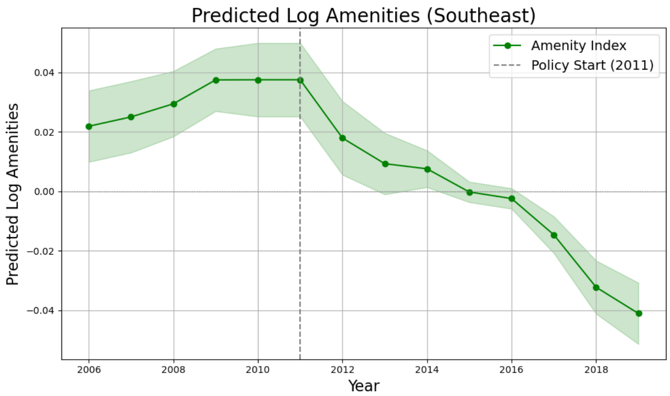

Figure 10: Amenity Plot

4 A Dynamic Structural Model

Environment

I consider an economy composed of N distinct regions, indexed by i and j.[9] Each region hosts a segmented labor market that separately accommodates three groups: high-skilled natives, low-skilled natives, and refugees. A continuum of firms operates competitively in each region, producing a final good using labor inputs. Firms employ a nested CES production technology, where substitution occurs first between low-skilled natives and refugees, and then between low-skilled and high-skilled workers. Following Eaton and Kortum (2002), productivity draws follow a Fréchet distribution with dispersion parameter θ.

Time proceeds in discrete intervals, denoted by $t = 0, 1, 2, \ldots$. All households have perfect foresight, but only Turkish households migrate, choosing locations dynamically based on beginning-of-period

[9] I switch notation here to index regions by i and j, rather than r as in the reduced-form section, to avoid confusion with other model subscripts.

labor supplies in each region and anticipated future migration patterns. Households face mobility frictions in the form of interregional moving costs and individual shocks that influence relocation choices. The household location choice problem shares structural features and underlying mechanisms with the framework developed in Caliendo et al. (2019). I begin by outlining the dynamic optimization problem households face when choosing where to locate, taking the evolution of real wages across space and time as given. Subsequently, I describe the static equilibrium that determines wages and prices in each region, conditional on local labor supply.

Consumer Preferences

At time $t = 0$, each region i is populated by a mass $L^i_{s,0}$ of households belonging to type s. Each household supplies one unit of labor inelastically and earns the prevailing competitive wage $w^i_{s,t}$. The per-period utility of a type s worker living in region i at time t is a function of three components: consumption of goods ($C^i_{s,t}$), housing services ($H^i_{s,t}$), and local amenities (b^i_t). The utility function takes the following form, where the parameter η_s captures the heterogeneity in households' preferences towards regional amenities.

$$U^i_{s,t} = \left(b^i_t\right)^{\eta_s} \left(\frac{C^i_{s,t}}{\lambda}\right)^{\lambda} \left(\frac{H^i_{s,t}}{1-\lambda}\right)^{1-\lambda}, \quad 0 < \lambda < 1, \; s = \{h, \ell, t\} \tag{1}$$

Building on Diamond (2016), I assume that the per capita local amenities in region i at time t decline with the presence of low-skilled workers (both natives and refugees) and improve with a larger share of high-skilled natives. Therefore, I model amenities as an endogenous outcome that depends on the ratio of high-skilled to low-skilled labor in each region. The elasticity of amenity supply is denoted by ϕ. I also refer to it as the congestion parameter in the model, as it captures how much the increase in refugees per region over time, i.e. the congestion, impacts amenities. Finally, ζ^i_t captures the exogenous component of the amenity level b^i_t.

$$b^i_t = \left(\frac{L^i_{h,t}}{L^i_{\ell,t} + L^i_{r,t}}\right)^{\phi} \cdot \zeta^i_t \tag{2}$$

The household's decision-making problem is dynamic. Households are forward-looking and discount future utility at a constant rate $\beta \geq 0$, and their migration choices involve spatial mobility costs.

Following standard assumptions in the literature, I assume that relocation costs $m_s^{i,j} \geq 0$ are additive, time-invariant, and vary by household type s as well as origin-destination pair (i, j); these costs are measured in utility terms. Each household also experiences an idiosyncratic preference shock $\varepsilon_{s,t}^j$ for each potential destination, introducing randomness into their location choices.

The sequence of household decisions unfolds as follows. At the start of each period, households observe prevailing economic conditions across all regions along with their own shock realizations. Those already residing in a region participate in the local labor market and earn the corresponding wage. An important thing is to note that, in the model, only the natives may relocate across regions, while refugees are assumed to remain in their initial location after arriving from Syria. This reflects Turkiye's temporary protection policy, which provides very limited internal mobility for Syrians. To move, a refugee must secure a job offer in another region, file a formal request, and wait for official approval, which is a process that is both bureaucratically and financially burdensome. The lack of funds further constrains their mobility, so refugees do not make dynamic migration decisions in the model and instead choose only their goods and housing consumption within the region where they reside. This is implemented by assigning them infinite migration costs $(m_r^{i,j} = \infty)$[10].

Formally, the value function for a type s worker residing in location i at time t reflects their earnings, utility, and expectations over future outcomes, while incorporating the migration costs $m_s^{i,j}$, the idiosyncratic preference shocks $\varepsilon_{s,t}^j$, the dispersion parameter ν, and the discount factor β.

$$v_{s,t}^i = log(U_{s,t}^i) + max_{j=\{1,\ldots,N\}} \left\{ \beta E[v_{s,t+1}^j] - m_s^{i,j} + \nu \varepsilon_{s,t}^j \right\} \tag{3}$$

In this expression, $v_{s,t}^i$ represents the expected lifetime utility of a type s household residing in region i at time t, where the expectation is taken over future realizations of the idiosyncratic shock. The parameter ν scales the variance of the idiosyncratic shocks. Households evaluate their current utility and consider all possible destinations, ultimately choosing the location that maximizes their expected future utility net of migration costs[11] and random taste shocks.

To simplify aggregation across heterogeneous households, I assume that the idiosyncratic prefer-

[10] We do observe Syrian refugee migration to other regions of Turkiye as well, after arriving at Southeast, only in more recent years. However, for the time frame of my study, it is plausible to assume no further migration of refugees within Turkiye after they settle into the Southeast.

[11] Migration costs are modeled as utility costs rather than direct expenditures, which implicitly assumes households can smooth consumption through perfect credit markets.

ence shocks ε are independently and identically distributed over time and follow a Type I Extreme Value distribution with zero mean. This structure enables closed-form expressions for expected values, facilitating tractable computation of household location decisions.

I let $V^i_{s,t} = E[v^i_{s,t}]$ denote the expected lifetime utility of a representative type s household currently residing in region i, where the expectation is taken over the preference shocks. Under this assumption, the expected utility satisfies the following expression:

$$V^i_{s,t} = log(U^i_{s,t}) + \nu log\left(\sum_{j=1}^{N} exp\Big(\beta V^j_{s,t+1} - m^{i,j}_s\Big)^{\frac{1}{\nu}}\right), \quad i,j = \{1,...,N\} \tag{4}$$

Equation (4) captures the idea that the value of living in a given region reflects both current-period utility and the expected gains from relocating in the future, i.e. the option value of migrating to another region in the next period. The term $V^i_{s,t}$ is interpreted either as the expected lifetime utility before the realization of the preference shocks or as the average utility level across type-s households in region i.

Under the assumption that idiosyncratic shocks follow an i.i.d. T1EV distribution, we can derive a closed-form analytical expression for migration flows between regions. Let $\mu^{i,j}_{s,t}$ denote the fraction of type s households relocating from region i to j, where the case $i = j$ represents those who choose to stay[12]. Then, following standard derivations in the literature, the migration share is given by:

$$\mu^{i,j}_{s,t} = \frac{exp\Big(\beta V^j_{s,t+1} - m^{i,j}_s\Big)^{\frac{1}{\nu}}}{\sum_{k=1}^{N} exp\Big(\beta V^j_{s,t+1} - m^{i,j}_s\Big)^{\frac{1}{\nu}}}, \quad s = \{h, \ell\},\ i,j = \{1,...,N\} \tag{5}$$

The expression in equation (5) reflects the intuitive result that regions offering higher expected utility, net of migration costs, will attract a larger share of movers. The parameter $1/\nu$ captures the responsiveness of migration flows to differences in expected value across destinations, effectively serving as migration elasticity. As noted earlier, the refugees are assumed to face prohibitively high migration costs within Turkiye ($m^{i,j}_r = \infty$), making their migration shares undefined under this formulation. Therefore, I accordingly set $\mu^{i,j}_{r,t} = 0$ for all $i \neq j$.

Equation (5) plays a central role in the model, as it fully determines how the spatial distribution of labor evolves over time. Specifically, the law of motion for labor of type s in region i is given by:

[12] The gross flows are inferred from the data in order to solve the model, as explained in Appendix B.

$$L^i_{s,t+1} = \sum_{j=1}^{N} \mu^{j,i}_{s,t} L^j_{s,t}, \quad s = \{h, \ell\},\ i, j = \{1, ..., N\} \tag{6}$$

This equilibrium condition describes how native high- and low-skilled workers are reallocated across regions over time. In contrast, the distribution of refugee labor is treated as exogenous and does not evolve through the migration mechanism outlined above.[13] Given the timing structure of the model, the labor supply in each region at time t is entirely determined by relocation decisions made in the previous period. With labor supply in hand, we now turn to the static side of the model and introduce the production environment that determines equilibrium wages through labor market clearing at each point in time.

Production

Output in region i at time t is generated using high-skilled native labor ($L^i_{h,t}$), low-skilled native labor ($L^i_{\ell,t}$), and refugee labor ($L^i_{r,t}$), according to the following Nested Constant Elasticity of Substitution (CES) production function:

$$q^i_t(L_{h,t}, L_{\ell,t}, L_{r,t}) = A^i \left[a^i_h {L^i_{h,t}}^{\rho} + a^i_\ell \left(\gamma^i_\ell {L^i_{\ell,t}}^{\alpha} + \gamma^i_r {L^i_{r,t}}^{\alpha} \right)^{\frac{\rho}{\alpha}} \right]^{\frac{1}{\rho}}, \quad i = \{1, ..., N\} \tag{7}$$

where α and ρ represent the elasticities of substitution within and across skill groups, respectively; A^i is the total factor productivity in region i[14]; and a^i_h, a^i_ℓ, γ_ℓ, and γ_r are input share parameters reflecting relative importance of each labor type in production, with $\gamma_\ell + \gamma_r = 1$.

Given the absence of significant internal trade barriers in Turkiye, I assume negligible trade frictions and allow goods to move freely across regions. This implies that product markets are fully integrated, leading to a common price for the final good across space and time. As a result, all regional prices are normalized to one.[15] Using the properties of the Fréchet distribution, the common price index can be expressed as:

$$P^i_t = \left(\sum_{i=1}^{N} (x^i_t)^{-\theta} (A^i_t)^{\theta} \right)^{-\frac{1}{\theta}} = 1,\ \forall i, t \tag{8}$$

[13] For the evolution of refugee labor, I feed the sequence of incoming refugees at $t = 1$ ($\{L^i_{r,1}\}$) into my dynamic model as an unanticipated shock, which is an observable in my data.

[14] Since the production side is not the focus of this paper and regional productivity does not directly affect migration decisions in the model, I keep productivity constant over time. Incorporating heterogeneous productivity growth could be an extension for future work.

[15] For tractability, I abstract from international trade and do not model imports or exports, so the final good price is normalized nationally.

where x_t^i denotes the unit cost of production in region i, associated with the nested CES production technology. The cost index takes the following form[16]:

$$x_t^i = \left[{a_\ell^i}^{\frac{1}{1-\rho}} \left(({\gamma_\ell^i}^{\frac{1}{1-\alpha}} {w_{\ell,t}^i}^{\frac{\alpha}{\alpha-1}} + {\gamma_r^i}^{\frac{1}{1-\alpha}} {w_{r,t}^i}^{\frac{\alpha}{\alpha-1}})^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\rho}{\rho-1}} + {a_h^i}^{\frac{1}{1-\rho}} {w_{h,t}^i}^{\frac{\rho}{\rho-1}} \right]^{\frac{\rho-1}{\rho}} \tag{9}$$

Market Clearing

Given that housing supply H^i is fixed in each region, the housing market clears when total housing demand equals supply. This condition implies the following, where r_t^i is the housing rent in region i and λ denotes the expenditure share on consumption (with $1-\lambda$ allocated to housing).

$$H^i = \frac{1-\lambda}{r_t^i} \sum_s w_{s,t}^i L_{s,t}^i \implies r_t^i = \frac{1-\lambda}{H^i} \sum_s w_{s,t}^i L_{s,t}^i, \quad s = \{h, \ell, r\},\ i = \{1, ..., N\} \tag{10}$$

Equilibrium wages and labor demand are determined by the firm's profit-maximizing behavior. Taking first-order conditions with respect to each labor input yields:

$$\frac{\partial (q_t^i(L_{h,t}^i, L_{\ell,t}^i, L_{r,t}^i) - \sum_s w_{s,t}^i L_{s,t}^i)}{\partial L_{s,t}^i} = 0, \quad s = \{h, \ell, r\},\ i = \{1, ..., N\} \tag{11}$$

These conditions determine the equilibrium demand for each labor type. Labor market clearing then requires that the supply of each labor type matches its demand in every region and time period. The right-hand side of equation (12) reflects the labor demand implied by the wage $w_{s,t}^i$, as determined from the first-order conditions above.

$$L_{s,t}^i = L(w_{s,t}^i), \quad s = \{h, \ell, r\},\ i = \{1, ..., N\} \tag{12}$$

Equilibrium

The endogenous state of the economy at any point in time is defined by the distribution of labor, $L_{h,t}, L_{\ell,t}, L_{r,t}$, across regions. The model features both constant and time-varying fundamentals. The only time-varying fundamental is the amenity vector $b_t = \{b_t^i\}_{i=1}^N$, while constant fundamentals include labor mobility costs $M = \{m_s^{i,j}\}_{i,j=1,s=h,\ell}^{N,N}$, regional housing stocks $H = \{H^i\}_{i=1}^N$, productivity levels

[16] The derivation of the input cost is detailed in Appendix C.

$A = \{A^i\}_{i=1}^N$, and skill-specific production intensities $a_s = \{a_s^i\}_{i=1,s=h,\ell}^N$, $\gamma_s = \{\gamma_s^i\}_{i=1,s=\ell,r}^N$. For notational convenience, I use $\Theta_t \equiv (b_t)$ to represent time-varying fundamentals and $\bar{\Theta} \equiv (M, H, A, a_s, \gamma_s)$ to denote time-invariant fundamentals. In addition, the model parameters include the consumption share λ, discount factor β, migration elasticity ν, and the labor substitution elasticities α and ρ.

Definition: Given initial labor allocations $\{L_{h,0}^i\}_{i=1}^N$, $\{L_{\ell,0}^i\}_{i=1}^N$, $\{L_{r,0}^i\}_{i=1}^N$, and a sequence of fundamentals $\{\bar{\Theta}, \Theta_t\}_{t=0}^\infty$, a sequential competitive equilibrium is a sequence of household value functions, wages, rents, and labor allocations $\left\{\{V_{s,t}^i, w_{s,t}^i, r_t^i, L_{s,t}^i\}_{i=1;\, s=h,\ell,r}^N\right\}_{t=0}^\infty$ that solves the households' dynamic problem, the firms' problem, and the markets clear.

To compute this equilibrium, I apply the dynamic-hat algebra method introduced by Caliendo et al. (2019). This approach expresses equilibrium conditions in changes rather than levels, allowing the model to be solved without requiring knowledge of the absolute level of exogenous fundamentals or assuming that the economy is initially in steady state. Instead, I condition the model on observable allocations in the data, which implicitly contain information about fundamentals, and match the economy's observed cross-section in the initial year $t = 0$. Using these observed allocations, I first compute a baseline transition path for the economy in the absence of refugee inflows, capturing its natural dynamics. Then, I introduce the refugee population into their initial host regions as an unanticipated shock at $t = 1$, and solve for the post-influx transition path, tracing out the general equilibrium adjustment across regions and skill groups over time.

5 Parameter Estimation

The model contains a number of parameters, some of which are calibrated based on values commonly used in the spatial and migration literature, while others are estimated using data. Specifically, I set the consumption expenditure share to be $\lambda = 0.62$, as in Diamond (2016). I set the discount factor as $\beta = 0.97$, the migration elasticity as $1/\nu = 0.5$, and the substitution parameter between high- and low-skilled as $\rho = 0.75$, following Caliendo et al. (2021). I assume that low-skilled natives and refugees are perfect substitutes, and therefore set their substitution parameter as $\alpha = 1$[17]. The parameters of

[17] Section 10 presents results using alternative values of α beyond the baseline case of $\alpha = 1$.

amenity supply elasticity ϕ, the skill-specific amenity tastes η_s, and the skill-specific migration costs κ_s are estimated using regional and migration data. Below, I present the estimation methodology using Simulated Method of Moments (SMM).

Joint Estimation with Simulated Method of Moments (SMM)

The parameter vector of interest is $\theta = [\eta_h, \eta_\ell, \kappa_h, \kappa_\ell, \phi]$, where η_s denotes the amenity taste parameter for skill group $s \in \{h, \ell\}$, κ_s is the migration cost parameter for that skill group, and ϕ is the elasticity of amenity supply with respect to the local skill composition. I estimate these parameters jointly using the Simulated Method of Moments (SMM), combining information from observed migration flows and amenities.

Migration Flow Moments

In the structural model, the share of individuals of skill s migrating from region i to j at time t is

$$\mu_{s,t}^{i,j} = \frac{\exp\big(\beta V_{s,t+1}^{j} - m_s^{i,j}\big)^{1/\nu}}{\sum_k \exp\big(\beta V_{s,t+1}^{k} - m_s^{i,k}\big)^{1/\nu}}.$$

Here $V_{s,t+1}^{j}$ denotes the continuation value in region j, which depends on wages, rents, and amenities, while $m_s^{i,j}$ represents the cost of migrating from i to j.

To build intuition, I unpack the structural migration share equation by specifying functional forms for both utility and migration costs. Indirect utility in region j depends on wages, rents, and amenities. Higher wages increase consumption, higher rents reduce housing affordability, and better amenities raise overall utility. Formally, $V_{s,t+1}^{i}$ includes terms proportional to $\ln(w_t^i)$, $\ln(r_t^i)$, and $\ln(b_t^i)$. For migration costs, I assume they are proportional to bilateral distance with a skill-specific sensitivity parameter, such that $m_s^{i,j} = \kappa_s \cdot \text{dist}^{i,j}$. These functional forms motivate the following reduced form regression for log bilateral migration rates:

$$
\begin{aligned}
\ln\left(\frac{F_{s,t}^{i,j}}{L_{s,t}^{i}}\right) &= \beta_s^{(0)} + \beta_s^{(1)}\ln(w_{s,t}^{i}) + \beta_s^{(2)}\ln(w_{s,t}^{j}) + \beta_s^{(3)}\ln\left(\frac{L_{s,t}^{j}}{L_{s,t}^{i}}\right) \\
&\quad + \beta_s^{(4)}\ln(b_t^{i}) + \beta_s^{(5)}\ln(b_t^{j}) + \beta_s^{(6)}\ln(r_t^{i}) + \beta_s^{(7)}\ln(r_t^{j}) \\
&\quad + \beta_s^{(8)}\ln(dist^{ij}) + \nu_i + \nu_j + \lambda_t \\
&\quad \forall\, s=\{h,\ell\},\ \forall\, i,j=\{1,...,N\},\ \forall\, t=\{2006,...,2019\} \qquad (13)
\end{aligned}
$$

This specification highlights the channels through which migration flows respond to observable variables. The coefficients on amenities $\beta_s^{(4)}$ and $\beta_s^{(5)}$ serve as the empirical counterparts to the amenity taste parameter η_s. Higher amenities at the destination raise inflows, reflected in a positive coefficient $\beta_s^{(5)}$, while higher amenities at the origin lower outmigration, reflected in a negative coefficient $\beta_s^{(4)}$. The coefficient on distance $\beta_s^{(8)}$ provides the empirical counterpart to the migration cost parameter, with a negative sign consistent with higher costs reducing flows. Coefficients on wages and rents, $\beta_s^{(1)}, \beta_s^{(2)}, \beta_s^{(6)}$, and $\beta_s^{(7)}$, reflect expenditure shares implied by the utility function and are pinned down through calibration of the consumption share parameter λ. The coefficient on relative destination size and the fixed effects, $\beta_s^{(3)}, \nu_i, \nu_j$, and λ_t, are included as controls and do not correspond to structural parameters.

Hence, only amenities and distance provide identifying moments for the amenity taste parameter (η_s) and the migration cost parameter (κ_s). Below, I present the three empirical moments that identify η_s and κ_s. I let $\bar{q}_{\eta_s}^{orig}$ and $\bar{q}_{\eta_s}^{dest}$ denote the empirical moments for η_s, and let $\bar{q}_{\kappa_s}$ denote the empirical moments for κ_s. Then, the empirical migration moments are given by the following regression coefficients:

$$
\bar{q}_{\eta_s}^{orig} = \hat{\beta}_s^{(4)}, \quad \bar{q}_{\eta_s}^{dest} = \hat{\beta}_s^{(5)}, \quad \bar{q}_{\kappa_s} = \hat{\beta}_s^{(8)}
$$

Correspondingly, I present the three simulated moments that identify η_s and κ_s. I let $q_{\eta_s}^{orig}(\eta_s)$ and $q_{\eta_s}^{dest}(\eta_s)$ denote the simulated moments for η_s, and let $q_{\kappa_s}(\kappa_s)$ denote the simulated moment for κ_s. Those moments implied by the model are given by:

$$
q_{\eta_s}^{orig}(\eta_s) = -\eta_s, \quad q_{\eta_s}^{dest}(\eta_s) = +\eta_s, \quad q_{\kappa_s}(\kappa_s) = -\kappa_s,
$$

This framework predicts that amenities enter symmetrically, with outflows responding negatively to origin amenities, and inflows responding positively to destination amenities which correspond to $-\eta_s$ and $+\eta_s$ respectively. Distance enters through the migration cost function, which is proportional to bilateral distance scaled by the skill-specific parameter κ_s, and therefore the simulated counterpart to the distance coefficient is $-\kappa_s$.

I also present the empirical and the simulated moments respectively for the remaining parameters of regression (13), below:

$$\bar{q}_1 = \hat{\beta}_s^{(1)}, \quad \bar{q}_2 = \hat{\beta}_s^{(2)}, \quad \bar{q}_6 = \hat{\beta}_s^{(6)}, \quad \bar{q}_7 = \hat{\beta}_s^{(7)}$$

$$q_1 = \hat{\beta}_s^{(1)}(\theta), \quad q_2 = \hat{\beta}_s^{(2)}(\theta), \quad q_6 = \hat{\beta}_s^{(6)}(\theta), \quad q_7 = \hat{\beta}_s^{(7)}(\theta)$$

These simulated responses are compared to their empirical counterparts, providing the basis for the SMM estimation. Hence the overall migration moment conditions become:

$$g_{\eta_s,\kappa_s}(\theta) = \begin{bmatrix} \hat{\beta}_s^{(4)} + \eta_s \\ \hat{\beta}_s^{(5)} - \eta_s \\ \hat{\beta}_s^{(8)} + \kappa_s \end{bmatrix}, \qquad g_{s'}(\theta) = \begin{bmatrix} \hat{\beta}_s^{(1)} - \hat{\beta}_s^{(1)}(\theta) \\ \hat{\beta}_s^{(2)} - \hat{\beta}_s^{(2)}(\theta) \\ \hat{\beta}_s^{(6)} - \hat{\beta}_s^{(6)}(\theta) \\ \hat{\beta}_s^{(7)} - \hat{\beta}_s^{(7)}(\theta) \end{bmatrix}$$

While the migration flow moments are written in terms of time-invariant regression coefficients, the underlying variation differs by parameter. The identification of η_s relies on both cross-sectional and temporal changes in amenities, whereas the identification of κ_s comes exclusively from cross-sectional variation in bilateral distances, which are constant over time.

Amenity Evolution Moments

The model also predicts how local amenities evolve with the skill composition of the labor force. Amenities in region i at time t are modeled as:

$$\ln b_t^i = \phi \cdot \ln\left(\frac{L_{h,t}^i}{L_{\ell,t}^i + L_{r,t}^i}\right) + \xi_i + \gamma_t.$$

I project the observed amenity indices, which I construct from household survey data using a PCA-based measure, onto the relative skill composition and fixed effects. Then, I use the predicted component of $\ln b_t^i$ explained by skill shares, i.e., $\ln \hat{b}_t^i$ to construct my empirical moments, which isolates the variation relevant for identifying ϕ.

The simulated moments are generated by applying the model-predicted relationship between amenities and skill composition for a candidate value of ϕ. For each trial value, the model predicts the evolution of amenities in every region and year given the observed relative skill shares and the fixed effects.

The moment condition matches the predicted amenity index from the data to its model-implied counterpart, as shown below. By matching the predicted component of observed amenities to the simulated predictions, I obtain empirical leverage to identify the elasticity parameter ϕ.

$$g_{\phi,t}^i(\theta) = \ln \hat{b}_t^i - \ln b_t^i(\phi) \quad \Longrightarrow \quad g_{\phi,t}^i(\theta) = \ln \hat{b}_t^i - \left[\phi \cdot \ln \left(\frac{L_{h,t}^i}{L_{\ell,t}^i + L_{r,t}^i} \right) + \xi_i + \gamma_t \right]$$

Stacked Moment Vector and Estimator

Collecting these conditions, the full moment vector is:

$$g(\theta) = \begin{bmatrix} g_{\eta_h,\kappa_h}(\theta) \\ g_{\eta_\ell,\kappa_\ell}(\theta) \\ g_{h'}(\theta) \\ g_{\ell'}(\theta) \\ g_{\phi,t}^i(\theta) \end{bmatrix}$$

In the case of migration flows, the empirical objects are regression coefficients that summarize variation across all origin–destination pairs, so the resulting moments are defined at the coefficient level and do not carry region indices. By contrast, the amenity evolution equation is matched directly to the panel of observed amenities across regions and years, which requires retaining the i, t subscripts in the moment conditions.

Finally, the SMM estimator solves $\hat{\theta} = \arg\min_\theta g(\theta)^\top W g(\theta)$, where the weighting matrix W is defined as the inverse of the variance–covariance matrix of the empirical moments. Since the stacked moment vector combines regression coefficients from the migration flow equations with region–time residuals from the amenity evolution equation, W takes a block diagonal form. The upper-left block corresponds to the covariance matrix of the empirical migration flow coefficients, while the lower-right block corresponds to the variance of the amenity evolution residuals. Formally, the optimal weighting matrix is

$$W = \begin{bmatrix} \Omega_\beta^{-1} & 0 \\ 0 & \Omega_\phi^{-1} \end{bmatrix},$$

where Ω_β denotes the covariance matrix of the migration flow coefficients across skill groups, and Ω_ϕ denotes the variance–covariance matrix of the amenity evolution moments across regions and years. In the first stage I set $W = I$, and in the second stage I re-estimate with this optimal weighting matrix to improve efficiency.

This procedure jointly identifies the key parameters by matching reduced-form migration elasticities with respect to amenities and distance, as well as the evolution of amenities with the skill composition of the labor force, to the predictions of the structural model. Table 9 summarizes the parameter and moments with their associated data sources.

Table 9: Summary of Moment Conditions Used in SMM Estimation

Moment Type	**Data Source**	**Parameters**
Skill-specific bilateral migration flows	TurkStat Internal Migration Statistics, skill-specific flows inferred using proportional allocation	η_h, η_ℓ, κ_h, κ_ℓ
Amenity levels across regions and time	PCA-based amenity index constructed from TurkStat household survey	ϕ

An important feature of the estimation strategy is that the amenity taste parameters (η_h, η_ℓ) and migration cost parameters (κ_h, κ_ℓ) are separately identified due to their distinct effects on migration behavior. The parameters κ_s determine the spatial decay of flows with respect to distance and are identified from cross-sectional variation in bilateral migration patterns across origin-destination pairs. In contrast, the parameters η_s govern how migration responds to changes in regional amenities over time and are identified from intertemporal variation in outmigration shares, particularly following the deterioration of local amenities in refugee-hosting regions. Thus, even when wages are held constant, worsening amenities should induce higher outmigration for skill groups with larger η_s, while flows between similarly amenitized regions decline more sharply with distance for groups with higher κ_s. This separation of spatial versus temporal variation allows for clean identification of both sets of parameters within the unified SMM framework.

Below, I describe a separate estimation strategy, where I implement OLS and NLS to estimate the amenity taste parameter (η_s) and the amenity supply elasticity (ϕ), and present the results. These latter estimates serve as interim estimates for ϕ and η_s for the results section of the paper, as incorporating the estimation results from SMM are in progress.

Amenity Supply Elasticity (ϕ), Using OLS

To obtain an interim estimate for ϕ, I rely on the structural equation for endogenous amenity evolution, i.e. $b_t^i = \left(\frac{L_{h,t}^i}{L_{\ell,t}^i + L_{r,t}^i}\right)^{\phi} \cdot \zeta_t^i$. Taking logarithms yields a linear relationship, $ln(b_t^i) = \phi \cdot ln\left(\frac{L_{h,t}^i}{L_{\ell,t}^i + L_{r,t}^i}\right)$. Using regional panel data on labor allocations and amenity indices constructed via principal component analysis (PCA), I estimate this equation by Ordinary Least Squares (OLS) and obtain $\hat{\phi} = 0.32$[18]. In a later extension of the model that incorporates a tax revenue channel affecting amenities, I introduce two separate parameters, ϕ_1, ϕ_2, one capturing the elasticity of amenities to changes in public spending, and the other to changes in congestion. The amenity evolution equation used for the model extension as well as the estimates for these parameters are reported in Appendix E.

Amenity Taste Parameter (η_s), Using NLS

The amenity taste parameter η_s captures how different household types value regional amenities. I obtain interim estimates for η_s, I use an inverse relationship between amenities and out-migration, i.e. $\mu_s^i = (b^i)^{-\eta_s}$. Here, μ_s^i denotes the out-migration share of type s from region i in 2012, the year following the initial refugee influx. This equation implies that better amenities reduce out-migration, and that higher values of η_s indicate greater sensitivity to amenity differences. Normalizing the refugee amenity taste to $\eta_r = 1.00$, I estimate the remaining parameters using Nonlinear Least Squares (NLS) and find $\eta_s = \{\eta_h, \eta_\ell, \eta_r\} = \{5.12, 3.40, 1.00\}$.

[18] To address potential endogeneity in the share $s_{it} = \ln L_{h,it} - \ln(L_{\ell,it} + L_{r,it})$, I employ 2SLS. High-skill variation is instrumented with pre-2006 university presence interacted with national enrollment growth, while low-skill+refugee variation is instrumented with pre-2011 network–based shift–share exposure, distance to border crossings $\times$ post, and early camp/registration capacity $\times$ post. Fitted values from these first stages form $\hat{s}_{it}$, which enters the amenity equation with region and year fixed effects. See Appendix D for details.

6 Results

6.1 Baseline

The initial findings of the model yield reduction in low-skilled natives' incomes under all amenity taste parameter specifications presented below. This finding of the model aligns with the earlier reduced form findings. Regarding the high-skilled, a rise in incomes is observed. However, it is lower in magnitude compared to the decrease in incomes of low-skilled. The figures below display time in years as the horizontal axis and the wage effects (%) as the vertical axis. The wage effects (%) are measured via using the value of the economic outcome y, with the shock of the refugee influx (*yRefShock*) and without the shock (*yNoShock*). Therefore the y-axis variable *yDiff* follows: $yDiff = \frac{yRefShock - yNoShock}{yNoShock} \cdot 100\%$. My model simulations are set to $t = 100$, i.e. 100 years, assuming infinitely lived households.

Below, the observed outcome y refers to wages for high-skilled natives shown by the blue line, and wages for low-skilled natives shown by the red line. These values are averages across the Southeast region. The sudden initial negative change in low-skilled wages in all scenarios slowly disappear as the change (%) goes back to zero in the long-run. However, the smaller sized sudden change, i.e. an increase, for high-skilled wages does not go back to zero even in the long run, which can be seen on the middle and rightmost plots of Figure 11. When high-skilled households value amenities more than the low-skilled ($\eta_h = 5.12 > \eta_\ell = 3.40$, and $\eta_h = 7.00 > \eta_\ell = 3.40$), the high-skilled natives observe a permanent increase in their wages in the long-run, causing increased inequality between different skill groups.

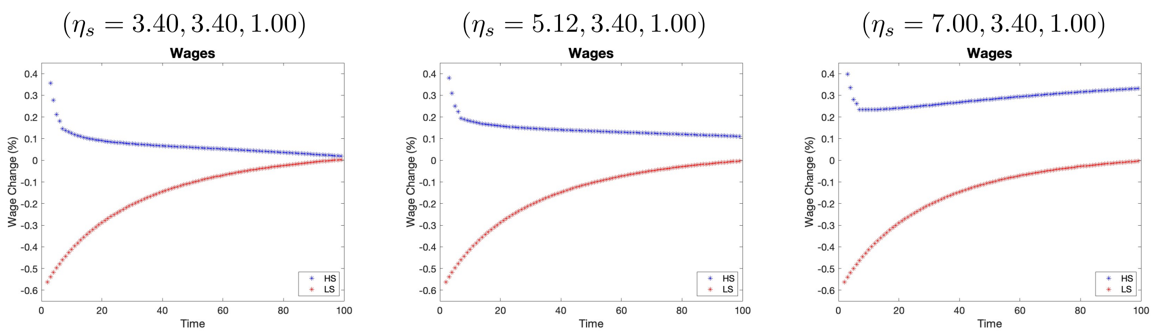

Figure 11: Effect of Refugees on Natives' Wage Evolution in the Southeast

Although the production function allows for substitution between high- and low-skilled labor ($\rho = 0.75$), the degree of substitutability is limited. Moreover, amenity deterioration drives high-skilled outmigration, reducing their local supply and raising their marginal productivity. This general equilibrium effect outweighs the weak substitution pressure, resulting in an increase in high-skilled wages in refugee-concentrated regions.

The non-monotonic pattern in high-skilled wages arises from general equilibrium adjustments in response to refugee-induced shocks. Initially, deteriorating amenities trigger high-skilled out-migration from the Southeast, shrinking the local high-skilled labor supply and raising wages. Over time, as the labor market rebalances and amenities partially recover due to lower congestion, the wage gains diminish, generating a non-monotonic adjustment path.

The baseline value $\eta_h = 5.12$ is estimated from the data using nonlinear least squares based on observed out-migration patterns. I use $\eta_h = 3.40$ as a lower bound, matching the estimated value for low-skilled households (leftmost plot), and $\eta_h = 7.00$ as an upper bound to test a scenario where high-skilled natives are even more responsive to amenity deterioration (rightmost plot). These alternative values help assess the robustness of the model's implications under varying degrees of amenity sensitivity. The leftmost plot of Figure 11 shows that the income gap created in the short run closes in the long run if the worker types were to have identical preferences in terms of their amenity tastes[19]. However, as mentioned earlier, the other two figures show that this the gap remains even in the long-run, under differentiated taste parameters. The gap widens with higher taste parameters for high-skilled labor. The larger the η_h, the sharper the utility decline of high-skilled workers, even with small amenity deteriorations. This leads to more aggressive out-migration of the high-skilled and thus greater income disparity between the two skill groups who stay in the Southeast.

6.2 Counterfactual: Reallocation of Refugees into Regions

This subsection explores a counterfactual scenario in which refugees are distributed evenly across Turkish regions, rather than being concentrated in the Southeast. Under this alternative allocation, the wage loss for low-skilled natives falls from 0.6% to 0.3%. Similarly, the wage gain for high-skilled

[19] The taste parameter for refugees is set to $\eta_r = 1.00$ in all specifications, as their amenity preferences affect only their current-period utility and do not influence relocation, due to them facing large migration costs ($m_r^{i,j} = \infty$).

natives declines from 0.4% to 0.3%. Overall, we still observe an increased wage inequality. While income inequality still rises, its magnitude is smaller relative to the baseline scenario.

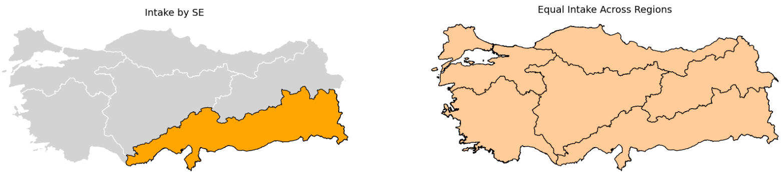

Figure 12: Reallocation Counterfactual

The next set of figures shows the temporal wage trajectories under this counterfactual, again across varying amenity taste specifications. The pattern of wage divergence remains similar, though the intensity is reduced. As in the baseline, higher amenity valuation by the high-skilled amplifies long-run inequality.

($\eta_s = 3.40, 3.40, 1.00$) ($\eta_s = 5.12, 3.40, 1.00$) ($\eta_s = 7.00, 3.40, 1.00$)

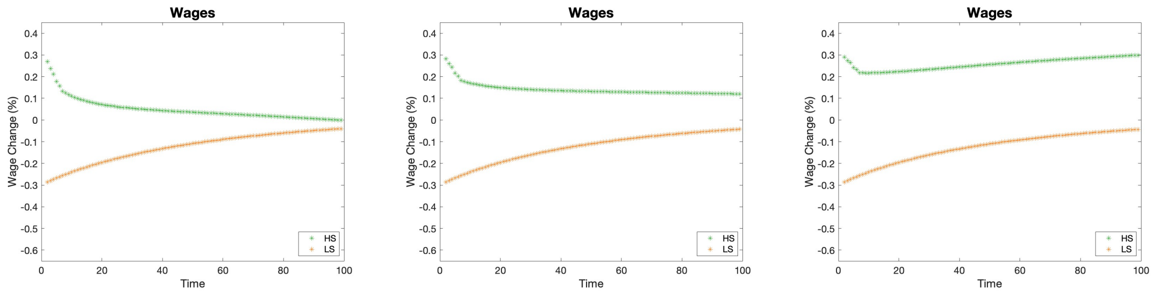

Figure 13: Effect of Redistribution Counterfactual on Natives' Wage Evolution in the Southeast

7 Extension: Tax Revenues

7.1 Baseline

This extension explores the extent to which amenity deterioration arises from congestion effects versus reductions in per capita public spending caused by the influx of refugees. Since refugees are not citizens, they are excluded from the formal tax base. As a result, in regions with significant refugee inflows, the tax revenue collected per capita declines. Because tax revenue funds local public goods, including education, health services, security, environmental protection, and cultural infrastructure (all of which are components of the amenity index), a decline in revenue implies reduced public goods provision and, thus, deteriorated amenities.

The key policy question is how much of the observed amenity deterioration is driven by overcrowding (e.g., more students per teacher), and how much is due to lower compensation (e.g., less income per teacher) or fewer resources available for public service provision.

In this extension of the paper, I adjust the amenity evolution, equation (2), as follows:

$$b_t^i = (T_t^i)^{\phi_1} \cdot (L_{T,t}^i)^{\phi_2} \cdot \zeta_t^i \tag{14}$$

where T_t^i denotes public spending in region i at time t, $L_{T,t}^i = L_{h,t}^i + L_{\ell,t}^i + L_{r,t}^i$ represents the total local population, and b_t^i is in per capita terms. The estimates of ϕ_1 and ϕ_2 are presented in the appendix.

7.2 Counterfactual: Subsidizing the Southeast via Government Transfers

I next examine a counterfactual scenario in which the government subsidizes the Southeast region to account for its disproportionately high refugee population. In the no-subsidy scenario (left panel of Figure 14), the government allocates public spending based solely on the native population. As a result, per capita public spending in the Southeast is significantly lower due to its inflated total population. In the first subsidy scenario (middle panel), I assume the government equalizes public spending per capita across all regions by including refugees in the allocation formula. This results in more funds being directed to the Southeast. In the second subsidy scenario (right panel), I double the per capita public spending directed to the Southeast relative to the first subsidy case, providing it with the most generous support.

Quantitatively, in the first subsidy scenario, per capita public spending in the Southeast increases by approximately \$1,250 per native, or 23% of the region's average annual income. In the second, more generous scenario, transfers rise to \$5,000 per native, approaching 91% of per capita income. These magnitudes serve to illustrate the impact of moderate versus ambitious fiscal interventions in refugee-hosting regions. In this counterfactual, the increased public spending shown in the middle and leftmost plots is assumed to be funded by external aid from international organizations.

Figure 15 illustrates the effects of these three scenarios on regional wage outcomes. Greater fiscal support for the Southeast helps reduce the wage gap and alleviates inequality.

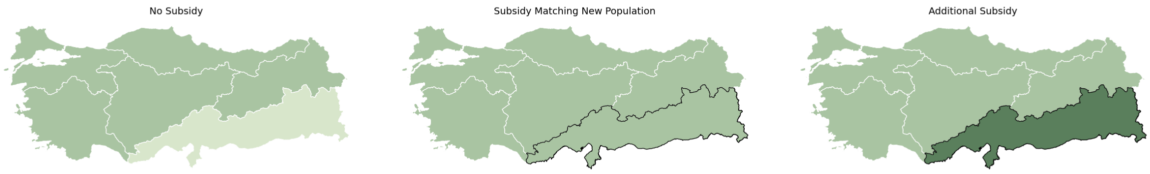

Figure 14: Money Transfer Counterfactual

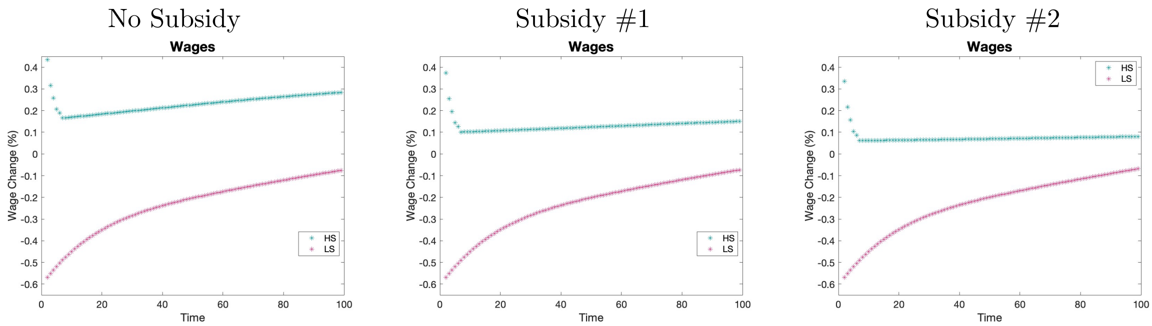

Figure 15: Effect of Subsidy Provision on Natives' Wage Evolution in the Southeast

7.3 Counterfactual: Subsidizing the Southeast through Tax Revenue

The previous counterfactual has studied the effect of government transfers to the Southeast which were assumed to be externally financed, such as through international aid. Therefore, Figure 15 has compared the cases of regular public spending from the Turkish government, moderate additional external help and more intense additional external help. These transfers entered the amenity equation as an exogenous monetary component, increasing public goods provision independently of the regional tax base. In this section, I consider an alternative scenario in which all transfers originate from the Turkish government, with no external financing. To this end, I retain the same monetary transfer variable (T_t^i) used in the previous counterfactual, but now assume it reflects only domestic. I then introduce an additional source of public spending, financed through income taxes on native households. Specifically, public spending in each region now includes a new term, $\tilde{T}_t^i = \tau \cdot I_t^i$, where τ is the income tax rate and I_t^i is total native income in region i at time t. This setup allows me to explore how redistributive taxation, layered on top of existing transfers, affects local amenity provision and wage dynamics. The new amenity evolution equation becomes:

$$b_t^i = (\tilde{T}_t^i + T_t^i)^{\phi_1} \cdot (L_{T,t}^i)^{\phi_2} \cdot \zeta_t^i \tag{15}$$

where $\tilde{T}_t^i = \tau \cdot I_t^i$ is the public spending coming through taxation, $I_t^i = w_{h,t}^i L_{h,t}^i + w_{\ell,t}^i L_{\ell,t}^i$ is the total income of native workers, τ is the tax rate applied uniformly across natives, and T_t^i represents public spending from the Turkish government which is not due to tax revenue generation. As this counterfactual studies the effects of different tax rates of amenity evolution, T_t^i here remains at the same value (as in the leftmost plot of Figure 15) across different tax rate variations.

To isolate the effects of redistributive taxation, I consider a scenario in which the high-skilled face an elevated marginal tax rate, defined by τ_h. Then, I increase the tax rate for high-skilled natives in all regions of Turkiye from $\tau_h = 0.3$ to $\tau_h = 0.4$ and $\tau_h = 0.5$, respectively, and redistribute the additional revenue exclusively to the Southeast. The total tax revenue redistributed is defined as:

$$T_t' = \sum_i (\tau_h - \tau) w_{h,t}^i L_{h,t}^i \tag{16}$$

and the amenity level in the Southeast is then:

$$b_t^{SE} = (\tau \cdot I_t^{SE} + T_t^{SE} + T_t')^{\phi_1} \cdot (L_{T,t}^{SE})^{\phi_2} \cdot \zeta_t^{SE} \tag{17}$$

This specification retains the same functional form for amenity evolution but adds a region-targeted transfer financed by progressive taxation. I analyze wage effects under varying tax rates for high-skilled workers, similar to the study in the previous section. The case with $\tau_h = 0.3$ mirrors the baseline (left most plot of Figure 15). Higher values of τ_h generate larger redistributive transfers. As expected, increasing the tax burden on high-skilled natives reduces wage inequality and improves amenities in the Southeast. Notably, when redistribution is sourced from high-income groups, the skill premium in the after-tax wages narrows more substantially compared to the counterfactual in Section 7.2.

Overall, the results from this extension resemble the findings of the prior counterfactual, with the high-skilled being relatively worse off. Increased support for the Southeast, whether through government transfers or tax-financed redistribution, helps preserve amenities and mitigate regional wage inequality. However, the source of funding matters for broader welfare considerations. Redistributive taxation reduces income inequality but also imposes a utility cost on the taxed group. In this case, higher taxes on the high-skilled may lower their value functions, diminishing their long-run welfare. This trade-off suggests that a mix of moderate government transfers and modest increases in tax contributions from high-income groups may be more effective than relying solely on either mechanism. Future work could quantify this welfare trade-off and explore optimal combinations of domestic taxation and external aid.

8 Robustness and Comparative Analysis

8.1 Changes in Overall Utilities Within the Southeast

Up to this point, the analysis has focused on how wages evolve in response to the refugee influx and how these changes affect the skill premium. In this section, I examine how the overall utility of native households, both high-skilled and low-skilled, is affected by the refugee influx. Importantly, the utility outcomes reported here refer specifically to those households who remain in the Southeast over time[20].

The findings are consistent across specifications of amenity evolution. One specification captures only congestion effects (equation (2)), while the other incorporates both congestion and public spending (equation (13)). In both cases, there is a decline in the utility of high skilled and low skilled natives who stay in the Southeast following the refugee influx. For low skilled households, this decline is primarily driven by lower wages. For high skilled households, it is the deterioration in local amenities that drives the decline in utility, even though their wages rise in response to labor reallocation. This implies that the wage gains are not large enough to fully compensate for the loss in amenities.

All counterfactuals discussed in Section 7 help reducing the magnitude of the decline in utilities. However, none of them changes the direction of the effect of the influx on household welfare. The equal reallocation of refugees across all regions, and the provision of subsidies to the Southeast through either government transfers or increased tax collection from natives, still cause utility reduction. However, the reduction is alleviated with these policy adjustments. For instance, for the low-skilled natives who

[20] Utilities integrate out the idiosyncratic shocks, so results reflect wages, amenities, and migration costs rather than selection on favorable ε draws among stayers.

continue to reside in the Southeast, the long-run decline in utility drops from approximately 6% in the baseline to 5.2% under the reallocation scenario, and to 4.5% under the subsidy scenario.

In summary, while the refugee influx leads to a reduction in the welfare of native households who remain in the Southeast, the impact can be meaningfully mitigated through policy interventions. The goal of the paper is to highlight that the same humanitarian aid could be provided to the refugees who are willing to join the labor force of Turkiye, by using a better allocation of existing national resources.

It is a fact that the country ends up paying for the adjustment costs due to the refugee integration, through lower low-skilled native wages, worsened amenities, and lower overall welfare during the adjustment period. This is an inevitable outcome for a country like Turkiye, specifically the Southeast of Turkiye, which lacks the skilled labor and the infrastructure to accommodate such integration. However, this does not mean that either the migrants (through receiving insufficient help) or the host country (through sharing their limited resources) ultimately has to suffer. The paper aims to emphasize how to implement better policies so that the policy implication becomes beneficial for both groups by lessening the short term burden on the host country as much as possible, while providing the necessary humanitarian aid to the ones in need.

8.2 Between Region Comparisons

Thus far, the focus has been on within-region dynamics in the Southeast, particularly regarding wage inequality. I now extend the analysis by comparing the effects of the refugee influx across multiple regions in Turkiye.

Congestion Model Specification

I begin with the congestion-only specification, where amenity evolution depends solely on the relative composition of high-skilled to low-skilled labor. The figure below shows the wage dynamics for three selected regions: the Southeast (region 6), Mid-Anatolia (region 3), and the Northwest (region 1). The Southeast results were previously presented in Section 6.1, while the latter two regions are presented here the first time. The regions of Mid-Anatolia and Northwest are chosen for comparison as they are among the primary destinations where high skilled natives relocate to in response to the refugee shock.

As shown in Figure 16, the regions receiving an inflow of high-skilled workers from the Southeast, the ones on the middle and left plots, experience a reduction in high-skilled wages due to the increased supply of skilled labor. This decline reaches approximately 0.3% in Mid-Anatolia and is even larger in the Northwest. In contrast, low-skilled wages increase in these receiving regions due to their relative scarcity. In the Northwest, the low-skilled wage increase is about 0.3%, and even more pronounced in Mid-Anatolia. Therefore, in these two regions, we see the exact opposite outcome compared to the case of the Southeast.

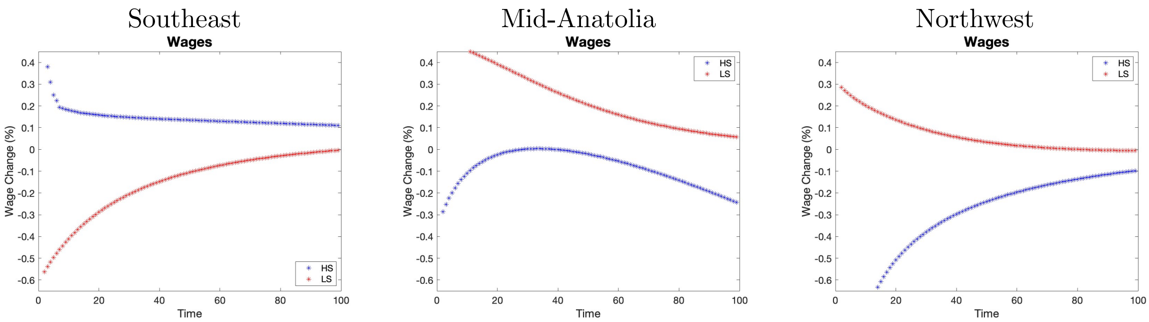

Figure 16: Opposite Pattern for Wages Changes in High-Skilled Receiving Regions

The Northwest gradually absorbs these changes over time, with both wage effects converging toward zero in the long run. This convergence is driven by its large population and greater economic capacity. Mid-Anatolia, however, continues to experience a persistent wage reduction for high skilled workers, approximately 0.25% in the long run, due to the lasting increase in its skilled labor supply.

Tax Model Specification

Next, I present results under the tax revenue specification, where amenity evolution depends not only on congestion but also on tax revenues collected and translated into public spending. I again show wage dynamics in the Southeast, Mid-Anatolia, and the Northwest.

Figure 17 closely resembles Figure 16 in that the refugee shock increases high-skilled wages in the Southeast while raising low-skilled wages in the other two regions. The effects on low-skilled wages in each region are nearly identical between this and the previous specification. This is expected, since these dynamics are driven primarily by relative labor supply and we do not observe a significant relocation pattern of the low-skilled between regions. In contrast, the inclusion of public spending in the amenity channel affects high-skilled wages more visibly, due to their stronger preferences for amenities.

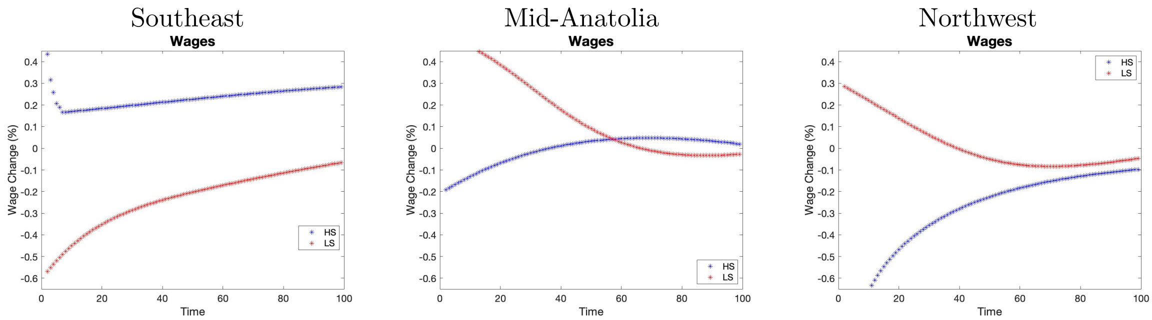

Figure 17: Opposite Pattern for Wages Changes in High-Skilled Receiving Regions

In the Southeast, the skill premium widens more under the tax revenue specification than under congestion alone. This suggests that the marginal benefit of public spending in the Southeast is insufficient to offset the amenity deterioration caused by the refugee inflow, leading more high-skilled workers to leave. As a result, high-skilled wages for those who remain increase even further. In Mid-Anatolia, the long-run wage effects for both skill groups converge toward zero, unlike in the congestion-only model. This indicates that the region does not receive as large a share of high-skilled migrants under the tax revenue specification, likely because its public spending effects are not as strong a pull factor. The results for the Northwest remain robust across both specifications. As the most economically dynamic region in Turkiye, containing Istanbul, it consistently receives the largest inflow of high-skilled migrants. In the short run, this leads to lower high-skilled wages and higher low-skilled wages. Over time, both wage effects converge back to their pre-shock levels as the labor market adjusts.

8.3 Different Substitution Parameters

In the baseline model, I assumed perfect substitutability between low-skilled native and refugees by setting the substitution parameter $\alpha = 1$. In this section, I relax that assumption and explore how results change under alternative values of α. Specifically, I consider two additional cases: $\alpha = 0.8$ and $\alpha = 0.6$. These values allow us to explore different assumptions about labor market competition between low-skilled natives and refugees. Since the substitution elasticity between high- and low-skilled natives is set at $\rho = 0.75$, the case with $\alpha = 0.6$ implies that low-skilled natives and refugees are less substitutable than high- and low-skilled natives. Conversely, the case with $\alpha = 0.8$ implies greater substitutability between the two low-skilled groups than between high- and low-skilled workers.

$\alpha = 1.0$ $\alpha = 0.8$ $\alpha = 0.6$

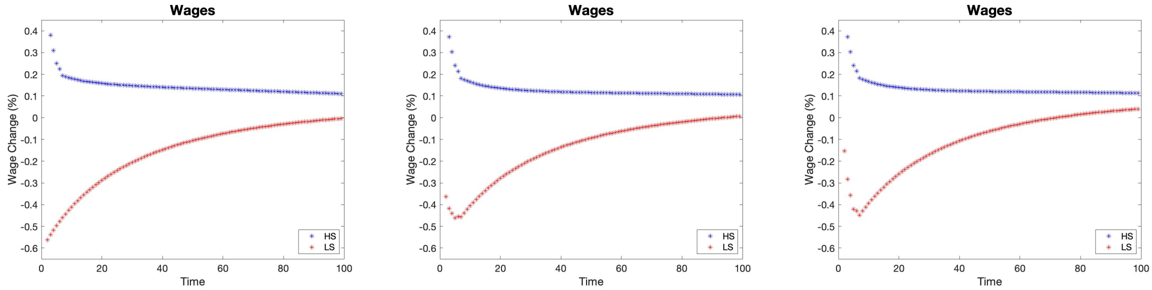

Figure 18: Smaller Initial Wage Drop for Low-Skilled with Lower Substitutability

As shown in Figure 18, reducing the degree of substitutability between refugees and low-skilled natives leads to a smaller negative impact on the wages of low-skilled natives in the Southeast. This is intuitive, as lower substitutability reduces the extent to which an influx of refugee labor depresses native wages.

These results highlight the importance of accurately estimating the substitution parameter α. With more detailed data on refugee wages, it would be possible to empirically estimate α, rather than imposing a value as in the baseline. A more precise estimate would in turn yield a more accurate assessment of the wage effects of the refugee shock. It is also important to note that even under a relatively low substitution parameter such as $\alpha = 0.6$, the model still predicts a reduction in the wages of low-skilled natives. This suggests that the qualitative finding, i.e. a negative wage effect for low-skilled natives following the refugee influx, is robust to a range of substitution elasticities.

9 Conclusion

Over the past decade, the skill wage premium in Turkiye, specifically in the Southeast, has shown a significant upward trend. This paper investigates one of the underlying drivers of this trend by linking it to the Syrian refugee influx that began after 2011. The analysis shows that the widening wage gap between high- and low-skilled workers in the Southeast can be attributed in large part to the outmigration of high-skilled natives from that region. The central question addressed is why native workers tend to relocate away from areas with high refugee concentrations.

The model presented identifies two key mechanisms behind this native outflow. The first is a congestion channel, captured in the baseline model, where increased population pressure reduces the quality of amenities. The second is a fiscal channel, introduced in the extension, where the arrival of non-taxpaying refugees reduces per capita public spending and further deteriorates local amenities.

The key finding is that concentrating refugee inflows in the Southeast exacerbates congestion, which in turn deteriorates local amenities and intensifies native outmigration. This congestion effect drives up the skill wage premium as high-skilled workers leave and low-skilled workers remain. I examine various counterfactual policy scenarios that alleviate this dynamic. In the first counterfactual presented in section 6.2, refugees are reallocated evenly across all regions rather than being concentrated in the Southeast. This reduces the congestion pressure and leads to a smaller skill wage premium in the Southeast. In the following counterfactuals presented in sections 7.2 and 7.3, which are based on the extension with the fiscal channel, the government increases public spending in the Southeast through targeted subsidies. This also reduces wage inequality, as improved amenities help retain high-skilled natives. All counterfactuals demonstrate that wage inequality in the Southeast can be significantly mitigated through either redistribution of refugee settlement or enhanced fiscal support.

These findings underscore the importance of designing more balanced and inclusive refugee policies, where inclusiveness refers to a more equitable geographic distribution of refugees across regions. In the case of Turkiye, where refugees were initially settled in one of the country's most underdeveloped regions, the economic consequences have been more severe. Policies that either distribute refugee populations more evenly or provide sufficient financial support to high-intake regions can allow the country to meet its humanitarian obligations without undermining its existing economic structure [21].

At the same time, it is important to recognize that refugee inflows may generate offsetting benefits alongside the costs documented here. One promising channel is consumer prices: by supplying labor in low-wage sectors such as agriculture, construction, and personal services, refugees may reduce the cost of basic goods and services. While my analysis does not incorporate price effects directly, future work could examine regional variation in food and service prices to assess whether refugee exposure slowed the growth of consumer prices. Embedding such a mechanism into the model would make it possible to evaluate welfare on both the income and expenditure sides, providing a more comprehensive picture of the refugee inflow's economic consequences.

Future research could also extend this analysis by incorporating additional shocks such as the COVID-19 pandemic, the 2023 earthquake that caused the death of approximately 50,000 people in

[21] By economic structure I refer not only to the strain on local amenities, but also to the associated outcomes of greater high-skilled out migration, reduced low-skilled native incomes, and higher housing rents.

the Southeast, and the fall of the Assad regime in 2025, which could lead to refugee repatriation. Integrating these shocks into the model and evaluating their separate effects would offer important insights for designing proactive and context-sensitive refugee policies in Turkiye and other developing countries with comparable institutional and infrastructural settings.

10 Potential Future Extensions

This study focuses on the evolution of local amenities through two main channels: congestion and tax revenue generation. It also examines how heterogeneous amenity preferences affect household value functions and migration decisions. Throughout the analysis, the production side of the model is held fixed, abstracting from sectoral variation and alternative labor interactions. Several extensions could enrich the analysis and offer further insight into regional and distributional impacts.

Production Function with Sector-Specific Complementarity:

A potential extension is to introduce multiple sectors within each region and allow the elasticity of substitution between high and low skilled labor to vary across them. This would capture sector specific complementarities where high and low skilled workers jointly raise productivity. The sectoral composition within a region would then shape how it adjusts to refugee inflows. Regions with industries that feature strong complementarities could attract high skilled workers despite deteriorating amenities, as complementarities raise their relative productivity and wages.

Consumer Price Effects

While the influx of Syrian refugees placed considerable pressure on labor markets, housing, and public amenities, an important offsetting channel operates through consumer prices. Refugees predominantly entered low-wage sectors such as agriculture, construction, and personal services. The expansion of labor supply in these activities reduced production costs, which may translate into lower local prices for goods and services consumed by natives. In principle, such price effects could mitigate some of the welfare costs faced by Turkish households in refugee-concentrated areas.

To examine this mechanism empirically, I would exploit regional variation in refugee exposure and link it to consumer price indices (CPIs). In particular, I would focus on price sub-indices for food and services, which are the sectors most directly affected by low-wage labor supply. A natural specification is:

$$\Delta lnP_{rt} = \beta_0 + \beta_1 syrian\_share_{rt} + \beta_2 X_{rt} + \lambda_t + \nu_r + \varepsilon_{rt}$$

where ΔlnP_{rt} is the change in the log price index in region r at time t, $syrian\_share_{rt}$ measures the refugee-to-population ratio, ν_r are region fixed effects, λ_t are year fixed effects, and X_{rt} includes time-varying controls such as regional employment or income. The parameter of interest, β_1, captures whether regions with greater refugee exposure experienced slower (or faster) growth in consumer prices relative to less-exposed regions. A negative estimate would suggest that refugees lowered local costs of living through their impact on low-wage production.

This analysis would highlight that refugee inflows generate both costs and benefits. While low-skilled natives may experience reduced wages, households could simultaneously benefit from lower prices in essential goods and services. Such distributional dynamics underscore that large migration shocks reshape the economy in multidimensional ways rather than producing uniformly adverse consequences.

I treat this section as a side extension rather than a central contribution, since my primary analysis focuses on labor markets, housing, and amenities. However, the consumer price channel represents an important dimension of refugee impacts and could be incorporated into the structural model as a future research direction. Embedding consumer price effects into the model would allow me to quantify the net welfare implications of refugee inflows, accounting for both income and expenditure margins. This integration would provide a more complete picture of the economic consequences of refugee settlement policies and redistribution counterfactuals.

Additional Counterfactuals:

Beyond structural model extensions, several policy-relevant counterfactuals could be explored using the current framework. One such scenario involves the COVID-19 outbreak, which led to sharp reductions in the use and perceived value of public amenities due to lockdowns. This offers an opportunity to assess how exogenous shocks to amenity values affect migration and labor market dynamics.

Another counterfactual considers the 2023 earthquake, which caused significant damage in Southeastern Turkiye and Northern Syria. Incorporating this shock would tighten housing supply in the affected regions, increasing rents even more and reinforcing outmigration. While this shock would likely amplify existing patterns, it is important to quantify its additional impact on regional outcomes.

Finally, a forward-looking extension could evaluate the consequences of a political shift in Syria, such as the fall of the Assad regime. If a significant share of Syrian refugees were to return, either voluntarily or through policy coordination, the resulting outflows could have substantial effects on Turkish labor markets, housing, and public services. Distinguishing between persistent and reversible impacts of refugee inflows would be valuable for shaping long-term refugee and integration policy.

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11 Appendix

Appendix A:

Incomes in Response to the Influx

$$ln\_income_{irt} = \beta_0 + \beta_1 syrian\_share_{rt} + \beta_2 H_{irt} + \lambda_t + \nu_r + \varepsilon_{rt}$$

	low-skill income	high-skill income
syrian share	-0.008***	-0.003
	(0.002)	(0.003)
age	0.263***	0.569***
	(0.009)	(0.021)
age squared	-0.016***	-0.030***
	(0.000)	(0.001)
household size	0.051***	-0.008
	(0.003)	(0.007)
Observations	86,296	18,872
R^2	0.135	0.186

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Effect of Influx on Annual Incomes

House Rents in Response to the Influx

$$ln\_annualrent_{irt} = \beta_0 + \beta_1 syrian\_share_{rt} + \beta_2 H_{irt} + \beta_3 X_{rt} + \lambda_t + \nu_r + \varepsilon_{rt}$$

Low-Skilled Rents

	(1) owner	(1) tenant	(2) owner	(2) tenant	(3) owner	(3) tenant
syrian share	0.010***	0.013***	0.008***	0.011***	0.008***	0.011***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)
house quality	0.253***	0.644***	0.273***	0.586***	0.236***	0.587***
	(0.002)	(0.007)	(0.003)	(0.009)	(0.003)	(0.009)
income			0.020***	0.044***	0.020***	0.044***
			(0.000)	(0.001)	(0.000)	(0.001)
health services			0.044***	-0.039	0.051***	-0.038***
			(0.007)	(0.012)	(0.007)	(0.012)
no pollution					-0.087***	-0.019
					(0.007)	(0.013)
no crime					-0.071***	0.012
					(0.010)	(0.017)
Observations	176,004	60,800	88,606	37,120	88,606	37,120
R^2	0.420	0.341	0.435	0.385	0.436	0.385

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effect of Influx on Low-Skilled Occupied House Rents

High-Skilled Rents

	(1) owner	(1) tenant	(2) owner	(2) tenant	(3) owner	(3) tenant
syrian_share	0.001	0.016	0.001	0.019**	0.001	0.020**
	(0.007)	(0.011)	(0.008)	(0.010)	(0.008)	(0.010)
house_quality	1.935***	2.366***	1.615***	1.678***	1.618***	1.678***
	(0.030)	(0.050)	(0.036)	(0.047)	(0.036)	(0.048)
income			0.027***	0.067***	0.027***	0.067***
			(0.001)	(0.001)	(0.001)	(0.001)
health_services			-0.039	-0.020	-0.036	-0.016
			(0.041)	(0.045)	(0.041)	(0.046)
no_pollution					-0.008	-0.081***
					(0.035)	(0.043)
no_crime					-0.036	0.093
					(0.049)	(0.060)
Observations	20,882	14,032	15,364	11,923	15,364	11,923
R^2	0.361	0.345	0.389	0.470	0.389	0.470

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Effect of Influx on High-Skilled Occupied House Rents

Migration Flows in Response to the Influx

$$ln\_flow_{ct} = \beta_0 + \beta_1 syrian\_share_{ct} + \beta_2 X_{ct} + \lambda_t + \nu_r + \varepsilon_{ct}$$

Low-Skilled Flows

	(1) inflow	(1) outflow	(2) inflow	(2) outflow	(3) inflow	(3) outflow
syrian_share	-0.002	0.003	-0.002	0.003	-0.004	0.002
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
income			-0.002	0.018	-0.008	0.033*
			(0.017)	(0.016)	(0.023)	(0.019)
house_quality			0.086**	0.012	0.083*	0.016
			(0.037)	(0.034)	(0.048)	(0.041)
education					0.111	-0.084
					(0.104)	(0.089)
health_services					-0.093	0.166
					(0.164)	(0.140)
Observations	154	154	154	154	121	121
R^2	0.950	0.924	0.952	0.925	0.956	0.932

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Effect of Influx on Migration Flows of Low-Skilled

High-Skilled Flows

	(1) inflow	(1) outflow	(2) inflow	(2) outflow	(3) inflow	(3) outflow
syrian_share	0.633	1.034***	0.904	1.132***	0.636	1.040***
	(0.816)	(0.304)	(0.835)	(0.312)	(1.050)	(0.362)
income			0.328	0.119	0.206	0.103
			(0.216)	(0.080)	(0.334)	(0.115)
house_quality			0.158	0.057	0.329	0.287
			(0.639)	(0.239)	(1.070)	(0.369)
education					1.063	-0.054
					(1.523)	(0.525)
health_services					-2.366	-0.900***
					(2.228)	(0.768)
Observations	170	170	170	170	137	137
R^2	0.366	0.629	0.376	0.635	0.378	0.663

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Effect of Influx on Migration Flows of High-Skilled

Appendix B:

Inferring Migration Flows

To apply the dynamic hat algebra framework, I first construct the initial labor allocation using TurkStat's Labor Force Statistics and infer bilateral annual gross migration flows from TurkStat's Internal Migration Statistics. While the dataset provides regional origin and destination flows and skill-specific totals for each region, it does not report pairwise flows disaggregated by skill.

To fill this gap, I infer skill-specific bilateral flows using a proportional allocation method based on destination population shares. Consider a stylized example with four regions: A (origin), and B, C, D (destinations). Let $T_{A,B}, T_{A,C}, T_{A,D}$ denote total flows from A to each destination, and let $HS_{A,RoC}$ $LS_{A,RoC}$ represent the total high skilled and low skilled outflows from A to the rest of the country. Now, I need to infer the skill-specific pairwise flows, denoted by $HS_{A,B}, HS_{A,C}, HA_{A,D}; LS_{A,B}, LS_{A,C}, LS_{A,D}$, where HS represents high-skilled flows and LS represents low-skilled flows. Letting x_i define the unknown shares of high skilled migration from origin A to each destination i; x_B, x_C, x_D must satisfy:

$$T_{A,B}x_B + T_{A,C}x_C + T_{A,D}x_D = HS_{A,RoC}$$

$$T_{A,B}(1 - x_B) + T_{A,C}(1 - x_C) + T_{A,D}(1 - x_D) = LS_{A,RoC}$$

By the proportionality assumption, which assumes the fraction of high skilled outflows to be proportional to destination populations, I solve for the unknown shares x_i using the known population destinations n_i:

$$\frac{x_B}{n_B} = \frac{x_C}{n_C} \implies x_B = \frac{n_B x_C}{n_C}, \qquad \frac{x_B}{n_B} = \frac{x_D}{n_D} \implies x_B = \frac{n_B x_D}{n_D}$$

This system of equations yields a unique solution for the skill-specific bilateral shares. Once the shares x_i are determined, skill-specific flows are inferred as:

$$HS_{A,B} = x_B \cdot T_{A,B}, \quad HS_{A,C} = x_C \cdot T_{A,C}, \quad HS_{A,D} = x_D \cdot T_{A,D}$$

$$LS_{A,B} = (1 - x_B) \cdot T_{A,B}, \quad LS_{A,C} = (1 - x_C) \cdot T_{A,C}, \quad LS_{A,D} = (1 - x_D) \cdot T_{A,D}$$

Appendix C:

Derivation for the Input Cost Function (x_t^i)

Rewrite the production function as $q_t^i = A^i[a_h^i {L_{h,t}^i}^\rho + a_\ell^i {v_{\ell,t}^i}^\rho]^{\frac{1}{\rho}}$, where $v_{\ell,t}^i = (\gamma_\ell^i {L_{\ell,t}^i}^\alpha + \gamma_r^i {L_{r,t}^i}^\alpha)^{\frac{1}{\alpha}}$.

The objective is to minimize $w_{h,t}^i L_{h,t}^i + p_{\ell,t}^i v_{\ell,t}^i$, subject to $q_t^i = A^i[a_h^i {L_{h,t}^i}^\rho + a_\ell^i {v_{\ell,t}^i}^\rho]^{\frac{1}{\rho}}$,

where $p_{\ell,t}^i$ denotes the payments to unskilled labor.

Therefore, the Lagrangian becomes:

$\mathcal{L} = w_{h,t}^i L_{h,t}^i + p_{\ell,t}^i v_{\ell,t}^i - \lambda(A^i[a_h^i {L_{h,t}^i}^\rho + a_\ell^i {v_{\ell,t}^i}^\rho]^{\frac{1}{\rho}} - q_t^i)$

The first order conditions are as follows:

F.O.C. with respect to $L_{h,t}^i$: $w_{h,t}^i = \lambda A^i (a_h^i {L_{h,t}^i}^\rho + a_\ell^i {v_{\ell,t}^i}^\rho)^{\frac{1-\rho}{\rho}} a_h^i {L_{h,t}^i}^{\rho-1}$

F.O.C. with respect to $L_{\ell,t}^i$: $p_{\ell,t}^i = \lambda A^i (a_h^i {L_{h,t}^i}^\rho + a_\ell^i {v_{\ell,t}^i}^\rho)^{\frac{1-\rho}{\rho}} a_\ell^i {v_{\ell,t}^i}^{\rho-1}$

Combining the two equations yields:

$$\implies \frac{w_{h,t}^i}{p_{\ell,t}^i} = \frac{a_h^i {L_{h,t}^i}^{\rho-1}}{a_\ell^i {v_{\ell,t}^i}^{\rho-1}} \implies \frac{{w_{h,t}^i}^{\frac{\rho}{\rho-1}}}{{p_{\ell,t}^i}^{\frac{\rho}{\rho-1}}} = \frac{{a_h^i}^{\frac{\rho}{\rho-1}} {L_{h,t}^i}^\rho}{{a_\ell^i}^{\frac{\rho}{\rho-1}} {v_{\ell,t}^i}^\rho}$$

$$\implies {w_{h,t}^i}^{\frac{\rho}{\rho-1}} {a_\ell^i}^{\frac{\rho}{\rho-1}} {v_{\ell,t}^i}^\rho = {p_{\ell,t}^i}^{\frac{\rho}{\rho-1}} {a_h^i}^{\frac{\rho}{\rho-1}} {L_{h,t}^i}^\rho$$

$$\implies {w_{h,t}^i}^{\frac{\rho}{\rho-1}} {a_h^i}^{\frac{1}{1-\rho}} a_\ell^i {v_{\ell,t}^i}^\rho + {p_{\ell,t}^i}^{\frac{\rho}{\rho-1}} {a_\ell^i}^{\frac{1}{1-\rho}} a_\ell^i {v_{\ell,t}^i}^\rho = {p_{\ell,t}^i}^{\frac{\rho}{\rho-1}} {a_\ell^i}^{\frac{1}{1-\rho}} a_h^i {L_{h,t}^i}^\rho + {p_{\ell,t}^i}^{\frac{\rho}{\rho-1}} {a_\ell^i}^{\frac{1}{1-\rho}} a_\ell^i {v_{\ell,t}^i}^\rho$$

Then, rewriting the right-hand side in terms of q_t^i gives:

$$\implies {a_\ell^i}^{\frac{1}{\rho}} v_{\ell,t}^i ({w_{h,t}^i}^{\frac{\rho}{\rho-1}} {a_h^i}^{\frac{1}{1-\rho}} + {p_{\ell,t}^i}^{\frac{\rho}{\rho-1}} {a_\ell^i}^{\frac{1}{1-\rho}})^{\frac{1}{\rho}} = {p_{\ell,t}^i}^{\frac{1}{\rho-1}} {a_\ell^i}^{\frac{1}{\rho(1-\rho)}} (q_t^i)$$

$$\implies {a_\ell^i}^{\frac{1}{\rho}} v_{\ell,t}^i K^{\frac{1}{\rho}} = {p_{\ell,t}^i}^{\frac{1}{\rho-1}} {a_\ell^i}^{\frac{1}{\rho(1-\rho)}} q_t^i \quad \& \quad {a_h^i}^{\frac{1}{\rho}} L_{h,t}^i K^{\frac{1}{\rho}} = {w_{h,t}^i}^{\frac{1}{\rho-1}} {a_h^i}^{\frac{1}{\rho(1-\rho)}} q_t^i,$$

where $K = ({w_{h,t}^i}^{\frac{\rho}{\rho-1}} {a_h^i}^{\frac{1}{1-\rho}} + {p_{\ell,t}^i}^{\frac{\rho}{\rho-1}} {a_\ell^i}^{\frac{1}{1-\rho}})^{\frac{1}{\rho}}$

Summing the two equations, one for low- and the other for high-skilled, in the line above,

$$\implies K^{\frac{1}{\rho}} (v_{\ell,t}^i p_{\ell,t}^i + L_{h,t}^i w_{h,t}^i) = q_t^i ({a_\ell^i}^{\frac{1}{1-\rho}} {p_{\ell,t}^i}^{\frac{\rho}{\rho-1}} + {a_h^i}^{\frac{1}{1-\rho}} {w_{h,t}^i}^{\frac{\rho}{\rho-1}})$$

$$\implies K^{\frac{1}{\rho}} x_t^i = q_t^i K \implies x_t^i = q_t^i K K^{-\frac{1}{\rho}} = K^{\frac{\rho-1}{\rho}} q_t^i$$

Plugging back K, we have the input cost function per unit as:

$$\implies x_t^i = ({a_\ell^i}^{\frac{1}{1-\rho}} {p_{\ell,t}^i}^{\frac{\rho}{\rho-1}} + {a_h^i}^{\frac{1}{1-\rho}} {w_{h,t}^i}^{\frac{\rho}{\rho-1}})^{\frac{\rho-1}{\rho}}, \text{ where } p_{\ell,t}^i = ({\gamma_\ell^i}^{\frac{1}{1-\alpha}} {w_{\ell,t}^i}^{\frac{\alpha}{\alpha-1}} + {\gamma_r^i}^{\frac{1}{1-\alpha}} {w_{r,t}^i}^{\frac{\alpha}{\alpha-1}})^{\frac{\alpha-1}{\alpha}}.$$

The derivation of $p_{\ell,t}^i$ follows the same structure for the derivation of x_t^i.

Derivation for the Time Changes of the Input Cost Function ($\dot{x}_{t+1}$)

$$\dot{x}^i_{t+1} = \frac{x^i_{t+1}}{x^i_t} = \left(\frac{ {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t+1}}^{\frac{\rho}{\rho-1}} \frac{ {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t}}^{\frac{\rho}{\rho-1}} }{ {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t}}^{\frac{\rho}{\rho-1}} } + {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t+1}}^{\frac{\rho}{\rho-1}} \frac{ {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t}}^{\frac{\rho}{\rho-1}} }{ {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t}}^{\frac{\rho}{\rho-1}} } }{ {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t}}^{\frac{\rho}{\rho-1}} + {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t}}^{\frac{\rho}{\rho-1}} } \right)^{\frac{\rho-1}{\rho}}$$

$$\Longrightarrow \left(\frac{ {\dot{w}^i_{h,t+1}}^{\frac{\rho}{\rho-1}} {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t}}^{\frac{\rho}{\rho-1}} + {\dot{p}^i_{\ell,t+1}}^{\frac{\rho}{\rho-1}} {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t}}^{\frac{\rho}{\rho-1}} }{ {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t}}^{\frac{\rho}{\rho-1}} + {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t}}^{\frac{\rho}{\rho-1}} } \right)^{\frac{\rho-1}{\rho}}$$

$$\Longrightarrow \left(\frac{ {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t}}^{\frac{\rho}{\rho-1}} }{ {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t}}^{\frac{\rho}{\rho-1}} + {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t}}^{\frac{\rho}{\rho-1}} } {\dot{w}^i_{h,t+1}}^{\frac{\rho}{\rho-1}} + \frac{ {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t}}^{\frac{\rho}{\rho-1}} }{ {a^i_h}^{\frac{1}{1-\rho}} {w^i_{h,t}}^{\frac{\rho}{\rho-1}} + {a^i_\ell}^{\frac{1}{1-\rho}} {p^i_{\ell,t}}^{\frac{\rho}{\rho-1}} } {\dot{p}^i_{\ell,t+1}}^{\frac{\rho}{\rho-1}} \right)^{\frac{\rho-1}{\rho}}$$

$$\Longrightarrow \dot{x}^i_{t+1} = (\xi^i_{h,t} {\dot{w}^i_{h,t+1}}^{\frac{\rho}{\rho-1}} + \xi^i_{\ell,t} {\dot{p}^i_{\ell,t+1}}^{\frac{\rho}{\rho-1}})^{\frac{\rho-1}{\rho}}$$

Appendix D:

IV Setup for the Estimation of the Amenity Supply Parameter (ϕ)

Second stage:

Define the log share $s_{it} \equiv \ln L_{h,it} - \ln\big(L_{\ell,it} + L_{r,it}\big)$, and estimate $\ln b_{it} = \phi\, \hat{s}_{it} + X_{it}\gamma + \mu_i + \tau_t + \varepsilon_{it}$,

where μ_i and τ_t are region and year fixed effects and errors are clustered by region.

First stages:

Treat both components of s_{it} as endogenous and estimate:

$$\ln L_{h,it} = \pi_{h,0} + \pi_{h,1} Z^H_{it} + X_{it}\delta_h + \mu_i + \tau_t + v_{h,it},$$

$$\ln\big(L_{\ell,it} + L_{r,it}\big) = \pi_{d,0} + \pi_{d,1} Z^{R_1}_{it} + \pi_{d,2} Z^{R_2}_{it} + X_{it}\delta_d + \mu_i + \tau_t + v_{d,it}.$$

Combine fitted values to form $\hat{s}_{it} = \ln \widehat{L_{h,it}} - \ln(\widehat{L_{\ell,it} + L_{r,it}})$.

Shifters:

1) High skill supply: $Z^H_{it} = \text{univ}_i 0 \times \text{enroll}_t$,

univ_i: index of pre-2011 university capacity in region i

enroll_t: national college enrollment at time t

2) Refugee exposure: $Z^{R_1}_{it} = \pi_{i0} \times S_t, \quad Z^{R_2}_{it} = \frac{1}{T_i} \times \mathbf{1}\{t \geq 2011\}$

π_{i0}: initial share of refugees in region i (right after the first influx)

S_t: total influx of refugees at time t,

$\frac{1}{T_i}$: inverse travel distance from the Syrian border to the Turkish region i

Appendix E:

Estimation of ϕ_1, ϕ_2

In order to estimate ϕ_1 and ϕ_2, I use the equation for the endogenous evolution of amenities in the tax revenue extension, i.e. $b^i_t = (T^i_t)^{\phi_1} \cdot (L^i_{T,t})^{\phi_2} \cdot \zeta^i_t$, where T^i_t represents public spending in region i at time t, and $L^i_{T,t} = L^i_{h,t} + L^i_{\ell,t} + L^i_{r,t}$. Taking logarithms, I have $ln(b^i_t) = \phi_1 ln(T^i_t) + \phi_2 ln(L^i_{T,t})$. Running an OLS using data on regional and time level data for labor allocations, taxes collected, and amenity indices constructed via PCA, I obtain $\phi_1 = 0.12$, and $\phi_2 = -0.10$. These are the parameter values I use to plot the changes in wages for the tax revenue extension throughout the paper.