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The Geography of Refugee Shocks

Abstract

This paper studies how refugee inflows affect receiving communities using highly disaggregated German administrative data at a 1km × 1km resolution. We develop a novel spatial equilibrium model that features two geographic levels, small neighborhoods and more aggregated local labor markets (LLMs). In the model, local displacement effects and impacts on house prices are closely linked to immigrationinduced changes in neighborhood-level amenities and LLM-level productivity. Our empirical results show that refugee inflows lead to a less than one-for-one relative population relocation in neighborhoods, indicating that refugees have a positive impact on local amenities. We also find relocation on the LLM-level to be less than one-for-one, suggesting that refugees also positively impact local productivity.

JEL-Codes: J15, R1

Keywords: Immigration; refugees; spatial equilibrium

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1 Albrecht Glitz, Universitat Pompeu Fabra, Barcelona School of Economics, and IPEG; Lukas Hörnig, RWI and RUB; Konstantin Körner, IAB; Joan Monras; Federal Reserve Bank of San Francisco and Universitat Pompeu Fabra, Barcelona School of Economics, CREI, and CEPR. *– We thank Katrin Sommerfeld for sharing data on county-level allocation quotas in Germany. We gratefully acknowledge financial support from the Leibniz Competition (K165/2018/Segregation and Regional Mobility). Albrecht Glitz gratefully acknowledges financial support from the Spanish Agencia Estatal de Investigación (AEI), through the Severo Ochoa Programme for Centres of Excellence in R&D (Barcelona School of Economics CEX2019-000915-S) and the Spanish Ministerio de Ciencia e Innovación and Agencia Estatal de Investigación (through Ramón y Cajal Grant RYC-2015-18806 and PID2020-114231RBI00/MICIN/AEI/10.13039/501100011033). Joan Monras gratefully acknowledges financial support from the Spanish Agencia Estatal de Investigación (AEI), through the Severo Ochoa Programme for Centres of Excellence in R&D (Barcelona School of Economics CEX2019-000915-S). The views in this paper do not necessarily reflect the views of the Federal Reserve System.This paper is still a work in progress, and we plan to expand its scope.* *– All correspondence to: Lukas Hörnig, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: lukas.hoernig@rwi-essen.de*

1 Introduction

Since 2010, the number of forcibly displaced people in the world has more than doubled, reaching 89.3 million at the end of 2021 (UNHCR, 2022). The impact of refugee migration, and immigration more broadly, on the receiving regions has been studied extensively, with much of the literature focusing on labor market impacts (see Dustmann et al., 2016; Edo, 2019; for recent surveys of the literature), voting behaviour (e.g. Steinmayr, 2021; or Moriconi et al., 2022) and impacts on crime (e.g. Bell et al., 2013; or Piopiunik and Ruhose, 2017). Most existing studies have in common that they are conducted on a fairly aggregate regional level such as municipalities, counties or commuting zones. Many of the impacts of immigration, however, are likely to occur very locally, for instance regarding housing prices and local amenities. Any such local effects are then likely to generate significant spillovers to other localities which are difficult to capture in standard spatial correlation studies.

In this paper, we shed further light on the channels through which immigration affects receiving communities and identify the key local factors that mediate such impacts. We start from the observation that in an economy in spatial equilibrium, i.e., where individuals are free to move across locations and the marginal individual is indifferent between living in one place or another, the allocation of population across locations depends exclusively on fundamentals, i.e., exogenous productivity and local amenity levels. If these fundamentals remain unaffected, a spatially heterogeneous inflow of immigrants should be fully absorbed by population movements that bring the economy back to its initial distribution of individuals across space. As explained in more detail below, we argue that deviations from this outcome are informative about how immigration affects different locations, and in particular, how it changes local amenity and productivity levels.

To guide our empirical analysis, we develop a novel spatial equilibrium model that features two geographic levels, neighborhoods and commuting zones. We estimate the key parameters of this model using granular German grid data at a 1km x 1km resolution and variation in local immigrant inflows due to the large refugee wave of the period 2015-2016 during which around 850,000 refugees, mainly from the Middle East, arrived in Germany. In our model, local labor markets (commuting zones) are composed of many neighborhoods (small grid cells). Workers decide which local labor market and, within those, which neighborhood to live in, something that we model using taste heterogeneity and a nested structure. Local labor markets are assumed to be perfectly competitive so that there is just one prevailing wage in each market that depends, in equilibrium, on this market's productivity. Neighborhoods, in turn, are heterogeneous, each offering different amenity levels.

Using this framework, we show that a refugee inflow into a given neighborhood should lead to a one-for-one relative labor relocation *unless* refugees have an impact on local amenities. If refugees improve amenities, displacement should be less than one-for-one,

with a gradient that depends on the local housing supply elasticity. In places where housing is more difficult to provide, for example in denser areas, the displacement should be stronger than in neighborhoods with more elastic housing supply. Similarly, we show that a refugee inflow into a given local labor market should lead to a one-for-one labor relocation, unless refugees affect either local amenities (measured using neighborhood level variation) or labor market productivity. Relocation should be less than one for one if, for example, immigrants have a positive impact on productivity.

To test the theoretical predictions of our model, we use a novel German data set, the IAB GridAB, which is compiled from the universe of German social security records and provides detailed information on local workforces on a 1km x 1km grid cell level. We merge these high resolution data with socioeconomic and real estate information from the RWI-GEO-GRID and RWI-GEO-RED data sets (RWI and microm, 2020; RWI and ImmobilienScout24, 2022a,b,c,d) which are both provided at the same granular level. Our combined data provide unique insights into local adjustment processes on a geographically highly disaggregated level.

We find positive but smaller than one-for-one displacement effects at the neighborhood level: for every 10 refugees arriving in a neighborhood, population increases on average by 4.95 individuals. According to our framework, this partial displacement indicates that refugees positively affect amenity levels in local communities (which might include various hard-to-observe dimensions such as pride to help refugees, valuation of diversity etc.). There is no statistically significant evidence that the arrival of refugees affects, on average, local housing rents. When distinguishing between denser and less dense areas, however, we find that the displacement effect is significantly larger in dense areas, where we observe close to full displacement as well as significant impacts on rental prices, with a 1 percent inflow of refugees increasing rents by 0.46 percent. These findings suggest that refugees have a positive impact on local amenities, which are partially capitalized into higher rental prices in more dense areas, as predicted by the model. Restrictions to housing supply limit the extent to which dense neighborhoods can benefit from agglomeration forces. At a more aggregate level, we find that refugee shocks lead to an increase in local labor market population, but again, by less than one for one. From the perspective of the model, this result is consistent with the idea that refugee supply shocks increase local average productivity, in line with recent work by Peters (2022).

The paper is structured as follows. In Section 2, we develop a novel spatial equilibrium model which guides our empirical analysis. In Section 3, we describe our data sources and provide some key summary statistics. Section 4 presents our main results for the impact of immigration on local population and rental prices as well as the heterogeneity analysis with respect to local housing supply elasticities. Section 5 concludes the paper.

Related Literature

We contribute to three distinct branches of the literature. First, there is a large literature estimating the "displacement" or "crowd-out" effects of immigration, i.e., the impact that immigration has on the number of natives in a location (see e.g. Card, 2001; Borjas, 2006; Peri and Sparber, 2011; Fernandez-Huertas et al., 2019; Amior, 2020). Most papers interpret displacement effects as evidence that immigration decreases the value of living in particular locations. As the conventional rationale goes, if natives respond to exogenous immigrant inflows by moving to other locations, it must mean that natives "dislike" the consequences of inflows. In practice, the presence or absence of "displacement" effects is also important for the credibility of research designs that compare locations receiving larger versus smaller immigrant-induced supply shocks. We challenge the conventional view by clarifying what displacement effects mean in the context of a spatial equilibrium model, tailored to our rich geographic data. We show that in a scenario where immigrants do not affect the fundamentals of the economy, the expected outcome is full displacement. Less than full displacement therefore indicates positive effects of immigration on fundamentals. Furthermore, we show how to use different geographic units to disentangle the effects of immigration on amenities and productivity, and how to use variation in the housing market to identify the beneficiaries of migrant shocks.

Second, we add to the literature that studies the effects of immigration on amenities and productivity, outcomes which are usually hard to observe. Mazzolari and Neumark (2011) show that immigration contributes positively and significantly to non-tradable sectors such as restaurants, whereas Card et al. (2012) find that residents' attitudes towards immigrants are largely driven by concerns about their potentially negative impacts on amenities. Peri (2011), Lewis (2012), Terry et al. (2022), and Peters (2022) study the impact of immigration on productivity and find that migration affects technology adoption and raises productivity at the local level. Our results are in line with this prior research but instead of providing evidence for one specific channel through which migrants affect amenities or productivity, we provide a general framework that allows us to relate population movements to overall amenity and productivity effects.

Finally, our paper contributes to the literature that studies the effects of immigration on housing markets. The consensus in this literature seems to be that immigration impacts rental price growth when looking at more aggregated data but is associated with rental price declines when looking at more disaggregated data (Saiz, 2007; Saiz and Wachter, 2011). The past literature has not investigated the heterogeneity of these results across local geographic units and has not related this to the effect of immigrants on local amenities and productivity.[1]

[1] Kürschner Rauck and Kvasnicka (2018) find a significant negative impact of the 2015 refugee inflows on residential housing rents in Germany. Contrary to our study, however, they look at very short-run impacts and exploit more aggregate county-level variation.

2 Model

In this section, we present a spatial equilibrium model with various geographic aggregations. At a more disaggregate level, we consider "neighborhoods" which is the relevant geography for housing markets. Neighborhoods differ in the amount of land available and their pleasantness in terms of amenities. Moreover, there is heterogeneity in the extent to which neighborhoods can expand their housing services. At a more aggregate geographic level, we consider local labor markets, i.e., units within which workers can easily commute. The purpose of the model is to relate displacement effects at various geographic aggregations to migration shocks and changes in the "fundamentals", defined as the exogenous productivity level of the local labor market and the exogenous amenity level of the neighborhood.

Location Choice

We consider an economy with C commuting zones or local labor markets. Each commuting zone has J_c neighborhoods or grids which are denoted by $j(c)$. Labor markets are integrated in that the wage received is independent of the neighborhood an individual lives in. Housing markets are specific to each neighborhood. Indirect utility in a location, $V_{j(c)}$, is given by

$$\ln V_{j(c)} + \varepsilon_{i,j(c)} = \ln Z_{j(c)} + \ln w_c - \beta \ln p_{j(c)} + \varepsilon_{i,j(c)},$$

where Z denotes amenities, w wages, and p housing prices (or, more generally, the local price index), and where the parameter β reflects the share of income spent on housing (or, more generally, on local non-tradables).

There are L workers in total deciding where to live. Workers have idiosyncratic preferences over the various local labor markets and neighborhoods in the economy. We denote these idiosyncratic taste shocks by $\varepsilon_{i,j(c)}$ and assume they are drawn from a generalized extreme value distribution (leading to a nested logit model). Under this assumption, we obtain the following location choice as a function of economic fundamentals and the variance of the idiosyncratic shocks in the two nests (the neighborhood and the local labor market):

$$\pi_{j(c)} = (\frac{V_c}{V})^{\frac{1}{\lambda}} (\frac{V_{j(c)}}{V_c})^{\frac{1}{\theta}},$$

where $\pi_{j(c)}$ denotes the fraction of workers that choose to locate in neighborhood $j(c)$, i.e., $\frac{L_{j(c)}}{L}$, and where

$$V_c = (\sum_j V_{j(c)}^{\frac{1}{\theta}})^{\theta}$$

denotes the expected utility of living in local labor market c, and

$$V = (\sum_c V_c^{\frac{1}{\lambda}})^{\lambda}$$

denotes the expected utility of living in the economy.

The parameters θ and λ govern the elasticity of substitution between neighborhoods and between local labor markets, respectively.

Tradable Output

We assume that labor markets are perfectly competitive. As such, firms maximize profits, given the following production function for tradable output:

$$Y_c = F(K_c, L_c) = \frac{A_c}{(1-\alpha)} K_c^{\alpha} L_c^{1-\alpha},$$

where K_c denotes capital and L_c is the number of workers in location c. Workers supply labor inelastically once they have decided to live in a particular location.

Profit maximization leads to the following (inverse) demand for labor:

$$w_c = A_c L_c^{-\alpha} K_c^{\alpha} \Rightarrow L_c = (\frac{A_c}{w_c})^{\frac{1}{\alpha}} K_c.$$

Tradable output is freely traded so that goods market clear at the economy level. This is given by

$$(1-\alpha)Y = (1-\alpha)\sum_c Y_c = \sum_c \sum_{j(c)} w_c L_{j(c)},$$

where Y is total tradable output and Y_c denotes the amount of tradable output produced in each local labor market.

Housing Sector

We assume a competitive housing sector that combines final (tradable) output and land using the following technology:

$$Y_{j(c)}^H = \varsigma_{j(c)}^{-\varsigma_{j(c)}} (Y_{j(c)})^{\varsigma_{j(c)}} (T_{j(c)})^{1-\varsigma_{j(c)}},$$

where $T_{j(c)}$ is the (fixed) amount of land available in each neighborhood and $1-\varsigma_{j(c)}$ the weight of land in the production of housing.

Profit maximization leads to the following housing supply equation:

$$Y_{j(c)}^H = T_{j(c)} (p_{j(c)})^{\gamma_{j(c)}},$$

where $p_{j(c)}$ denotes local house prices and $\gamma_{j(c)} = \frac{\varsigma_{j(c)}}{1-\varsigma_{j(c)}}$ the housing supply elasticity.

The demand for housing is given by $\beta \frac{w_c}{p_{j(c)}} L_{j(c)}$ since we implicitly assumed a Cobb-Douglas utility function over the tradable and non-tradable goods in the economy when formulating the indirect utility function. Market clearing in the housing market is then given by the following equation:

$$T_{j(c)}(p_{j(c)})^{\gamma_{j(c)}} = \beta \frac{w_c}{p_{j(c)}} L_{j(c)}.$$

Equilibrium

Local Economies

The equilibrium in this economy involves three maximization problems. First, workers optimally choose where to live. Second, producers of tradables decide how much to produce, and third, producers of non-tradables decide how many housing services to provide in each location. These three optimizations problems generate a system of three equations and three unknowns for each neighborhood, linked to each other at the local labor market level by both the labor demand and the labor supply decisions, and linked across local labor markets by the labor supply equations. More explicitly, the system is defined by:

$$L_{j(c)} = (\frac{V_c}{V})^{\frac{1}{\lambda}} (\frac{V_{j(c)}}{V_c})^{\frac{1}{\theta}} L \tag{1}$$

$$\sum_{j(c)} L_{j(c)} = (\frac{A_c}{w_c})^{\frac{1}{\alpha}} K_c \tag{2}$$

$$T_{j(c)}(p_{j(c)})^{1+\gamma_{j(c)}} = \beta w_c L_{j(c)} \tag{3}$$

with exogenous variables given by $\{\gamma_{j(c)}, Z_{j(c)}, T_{j(c)}, A_c\}$ and endogenous variables by $\{L_{j(c)}, p_{j(c)}, w_c\}$, where we abstract from whether K_c is fixed or supplied elastically.

Aggregate Economy

Using the three optimality conditions, this economy admits a simple expression for aggregate output. Combining the labor supply equation with the market clearing condition we obtain:

$$(1-\alpha)Y = \sum_c w_c L_c = VL \sum_c (\frac{L_c}{L})^{1+\lambda} \bar{Q}_c = VL\bar{Q} \Rightarrow V = (1-\alpha)\frac{Y/L}{\bar{Q}},$$

where $Q_{j(c)} = p_{j(c)}^{\beta}/Z_{j(c)}$ and $\bar{Q}_c = (\sum_j Q_{j(c)}^{-\frac{1}{\theta}})^{-\theta}$. The last expression shows that aggregate welfare is equal to GDP per capita deflated by the aggregate price index.

Combining this expression with the labor supply equation, we obtain:

$$w_c = (\frac{L_c}{L})^{\lambda} V \bar{Q}_c = (\frac{L_c}{L})^{\lambda} (1-\alpha) \frac{Y}{L} \frac{\bar{Q}_c}{\bar{Q}}.$$

Inserting this expression back into the labor demand equation leads to:

$$L_c = (\frac{A_c}{w_c})^{\frac{1}{\alpha}} K_c = (\frac{A_c}{(\frac{L_c}{L})^{\lambda}(1-\alpha)\frac{Y}{L}\frac{\bar{Q}_c}{\bar{Q}}})^{\frac{1}{\alpha}} K_c \Rightarrow L_c^{\alpha+\lambda} = \frac{L}{Y}\frac{L^{\lambda}}{(1-\alpha)}(A_c\frac{\bar{Q}}{\bar{Q}_c})K_c^{\alpha}$$

$$\Rightarrow L_c = [\frac{L}{Y}\frac{L^{\lambda}}{(1-\alpha)}(A_c\frac{\bar{Q}}{\bar{Q}_c})K_c^{\alpha}]^{\frac{1}{\alpha+\lambda}}.$$

Aggregating up across local labor markets:

$$L = \sum_c [\frac{L}{Y}\frac{L^{\lambda}}{(1-\alpha)}(A_c\frac{\bar{Q}}{\bar{Q}_c})K_c^{\alpha}]^{\frac{1}{\alpha+\lambda}} = (\frac{L}{(1-\alpha)Y})^{\frac{1}{\alpha+\lambda}} L^{\frac{\lambda}{\alpha+\lambda}} \sum_c [(A_c\frac{\bar{Q}}{\bar{Q}_c})K_c^{\alpha}]^{\frac{1}{\alpha+\lambda}}$$

As a result:

$$(1-\alpha)^{\frac{1}{\alpha+\lambda}}(\frac{Y}{L})^{\frac{1}{\alpha+\lambda}} L^{\frac{\alpha}{\alpha+\lambda}} = \sum_c [(A_c\frac{\bar{Q}}{\bar{Q}_c})K_c^{\alpha}]^{\frac{1}{\alpha+\lambda}}$$

which can be re-expressed as:

$$Y = \frac{1}{1-\alpha} L^{1-\alpha} \left(\sum_c [(A_c\frac{\bar{Q}}{\bar{Q}_c})K_c^{\alpha}]^{\frac{1}{\alpha+\lambda}} \right)^{\alpha+\lambda} \tag{4}$$

This expression helps us aggregate the various local economies into an aggregate production function.

From this model, we can now derive various estimation equations.

Neighborhood Level Regressions

From the market clearing condition in the housing market we obtain:

$$p_{j(c)} = \delta_c \left(\frac{L_{j(c)}}{T_{j(c)}} \right)^{\frac{1}{1+\gamma_{j(c)}}},$$

where δ_c is a combination of variables that are determined at the local labor market level.

From the location choice model we obtain:

$$L_{j(c)} = \kappa_c (Z_{j(c)})^{\frac{1}{\theta}} p_{j(c)}^{-\frac{\beta}{\theta}}.$$

Combining the last two equations gives:

$$L_{j(c)} = \nu_c (Z_{j(c)})^{\frac{1}{\theta}} \left(\frac{L_{j(c)}}{T_{j(c)}} \right)^{-\frac{\beta}{\theta(1+\gamma_{j(c)})}} = \nu_c^{\frac{\theta(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}} (Z_{j(c)})^{\frac{(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}} (T_{j(c)})^{\frac{\beta}{\theta(1+\gamma_{j(c)})+\beta}},$$

where ν_c is a combination of local labor market aggregates (δ_c and κ_c).

Taking logs we obtain:

$$\ln L_{j(c)} = \frac{\theta(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}\ln \nu_c + \frac{(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}\ln Z_{j(c)} + \frac{\beta}{\theta(1+\gamma_{j(c)})+\beta}\ln T_{j(c)}. \quad (5)$$

This equation shows that the number of workers living in neighborhood j in local labor market c depends on three factors. Neighborhoods in better local labor markets (higher ν_c), with better amenities (higher $Z_{j(c)}$) and more available land (higher $T_{j(c)}$) attract more workers. The impact of changes in the attractiveness of the local labor market and the neighborhoods' amenities is mediated by the housing supply elasticity. In particular, the coefficient in front of $\ln \nu_c$ lies between $\frac{\theta}{\theta+\beta}$ (<1) if housing supply is perfectly inelastic ($\gamma_{j(c)} = 0$) and 1 if housing supply is perfectly elastic ($\gamma_{j(c)} = \infty$), so neighborhoods with more inelastic housing supply experience less of a population increase with improving labor market conditions. Similarly, the coefficient in front of $\ln Z_{j(c)}$ lies between $\frac{1}{\theta+\beta}$ if housing supply is perfectly inelastic ($\gamma_{j(c)} = 0$) and $\frac{1}{\theta}$ if housing supply is perfectly elastic ($\gamma_{j(c)} = \infty$). Improvements in amenities thus lead to larger population adjustments in neighborhoods where housing supply is more elastic.

The population in a given neighborhood can be decomposed into the native population ($N_{j(c)}$) and the refugee population ($M_{j(c)}$):

$$\ln N_{j(c)} = \frac{\theta(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}\ln \nu_c + \frac{(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}\ln Z_{j(c)} + \frac{\beta}{\theta(1+\gamma_{j(c)})+\beta}\ln T_{j(c)} - \ln(1+\frac{M_{j(c)}}{N_{j(c)}}).$$

Subtracting the native allocation in the period prior to the refugee shock (where $M_{j(c)} = 0$), we obtain:

$$\Delta \ln N_{j(c)} = \frac{\theta(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}\Delta \ln \nu_c + \frac{(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}\Delta \ln Z_{j(c)} - \ln(1+\frac{M_{j(c)}}{N_{j(c)}}). \quad (6)$$

This equation shows that, once we condition on the potentially heterogeneous effects that changes in labor markets may have in each neighborhood, natives should relocate one for one with the refugee shock unless the refugees affect local living conditions. In practice, we can account for the term $\frac{\theta(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}\Delta \ln \nu_c$ with a local labor market fixed effect interacted with a flexible proxy of local housing supply elasticities. Importantly, if refugees have a positive impact on local living conditions then, relocation should be less than one for one. This is our test of whether refugee shocks positively or negatively affect local neighborhoods' unobservable amenities.

Equation 6 implies some interesting heterogeneity across locations. If a refugee shock affects $Z_{j(c)}$ positively and homogeneously, then this equation says that there should be more displacement in neighborhoods with inelastic housing supply than in neighborhoods with elastic housing supply. We test this prediction by estimating the impact of immigration separately for neighborhoods with different population densities, assuming that denser neighborhoods have lower housing supply elasticities.

To the extent that refugees affect $Z_{j(c)}$, they will also affect housing prices:

$$\Delta \ln p_{j(c)} = \Delta\eta_c + \frac{\theta}{\theta(1+\gamma_{j(c)})+\beta}\Delta \ln \nu_c + \frac{1}{\theta(1+\gamma_{j(c)})+\beta}\Delta \ln Z_{j(c)}. \tag{7}$$

Under the assumption that refugees have a homogeneous effect on local amenities, we can divide the respective point estimates from our population and house price regressions to obtain an estimate of the average housing supply elasticity.[2]

Local Labor Market Regressions

Starting from the labor supply equation and summing over neighborhoods within each local labor market we obtain

$$L_c = (\frac{V_c}{V})^{\frac{1}{\lambda}} L,$$

which can be re-written as:

$$\ln L_c = \delta + \frac{1}{\lambda}(\ln w_c - \ln \bar{Q}_c).$$

We can combine this expression with the labor demand equation to obtain:

$$\ln L_c = \nu + \frac{1}{\lambda+\alpha}(\ln A_c + \alpha \ln K_c - \ln \bar{Q}_c).$$

Now, we can use the refugee shock as before:

$$\ln N_c = \nu + \frac{1}{\lambda+\alpha}(\ln A_c + \alpha \ln K_c - \ln \bar{Q}_c) - \ln(1+\frac{M_c}{N_c}).$$

Taking the difference between the period before and after the refugee shock in each local labor market, we obtain:

$$\Delta \ln N_c = \frac{1}{\lambda+\alpha}[\Delta \ln A_c - \Delta \ln \bar{Q}_c] - \ln(1+\frac{M_c}{N_c}), \tag{8}$$

where we have assumed fixed K_c.

We can now apply the same logic as before. If refugees do not have any direct effect on local amenities or house prices (which would affect $\bar{Q}_c$) or local labor market productivity (A_c), then population should relocate one for one at the local labor market level. We can use this to estimate the effect of refugees on unobserved productivity in each local labor market.

[2]Our main estimation equation for population changes is $\Delta \ln L_{j(c)} = \alpha_c + \beta_1 \frac{M_{j(c)}}{L_{j(c)}} + \varepsilon_{j(c)}$. From Equation 5, $\widehat{\beta}_1 = \frac{\partial \Delta \ln L_{j(c)}}{\partial (M_{j(c)}/N_{j(c)})} = \frac{(1+\gamma_{j(c)})}{\theta(1+\gamma_{j(c)})+\beta}\frac{\partial \Delta \ln Z_{j(c)}}{\partial (M_{j(c)}/N_{j(c)})}$. Our main estimation equation for house prices is $\Delta \ln p_{j(c)} = \alpha'_c + \beta_2 \frac{M_{j(c)}}{L_{j(c)}} + \varepsilon'_{j(c)}$. From Equation 7, $\widehat{\beta}_2 = \frac{\partial \Delta \ln p_{j(c)}}{\partial (M_{j(c)}/N_{j(c)})} = \frac{1}{\theta(1+\gamma_{j(c)})+\beta}\frac{\partial \Delta \ln Z_{j(c)}}{\partial (M_{j(c)}/N_{j(c)})}$. The ratio $\widehat{\beta}_1/\widehat{\beta}_2$ is thus equal to $1+\gamma_{j(c)}$.

3 Data

Our empirical analysis is based on three distinct data sets whose unit of observation is the 1km x 1km grid cell. The data sets contain information on the socioeconomic and demographic composition of the grid cells (RWI-GEO-GRID, RWI and microm, 2020), housing information from the housing listings of Immoscout24 (Germany's largest online marketplace for housing search; RWI-GEO-RED, RWI and ImmobilienScout24, 2022a,b,c,d), and labor market information from the IAB GridAB. The latter is a newly compiled data set by the Institute for Employment Research (IAB).[3] An early version of it has already been used by, e.g., Ostermann et al. (2022). The data set covers Germany's populated areas at a 1km x 1km grid level, approximately 225,000 grids, over the period 2000-2017. It is based on the Integrated Employment Biographies which comprise the universe of workers subject to social security contributions in Germany, marginally employed workers, unemployment benefit receivers, and individuals who reported seeking a job, in total approximately 40 million individuals per year. The definition of grid cells is based on the Lambert projection and follows the European INSPIRE regulation, allowing us to merge the labor market information with the other grid level data sets.

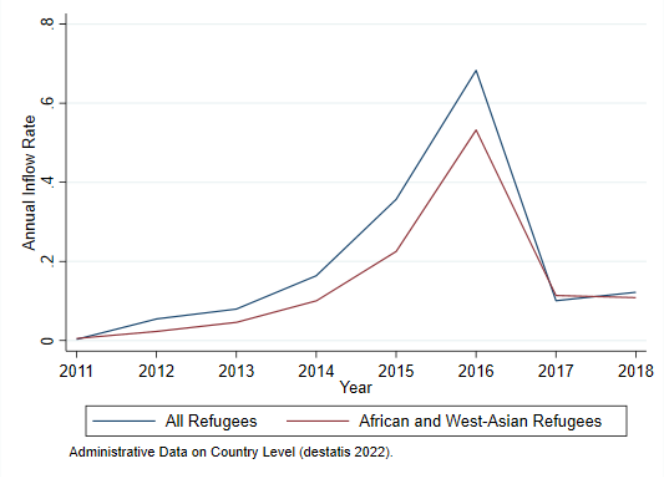
The RWI-GEO-GRID and the RWI-GEO-RED data sets are hosted by the Research Data Center Ruhr at RWI - Leibniz-Institute for Economic Research and available for non-commercial research as scientific use files. Information on the socioeconomic and demographic composition of grid cells in the RWI-GEO-GRID data is originally collected from Micromarketing-Systeme und Consult GmbH (microm), a commercial micro- and geomarketing provider. For a more extensive description of the data, see Breidenbach and Eilers (2018). The RWI-GEO-RED includes all listings of the online portal immoscout24, which is the market leader in Germany for online apartment and house listings. The data set includes rich information on object characteristics and, depending on the type (for sale/for rent), the listing prices or rents. The housing ads are geo-referenced at the 1km x 1km grid level. For a more extensive description of the data, see Schaffner (2020).

Sample Selection

Due to data security reasons, there is limited information in the RWI-GEO-GRID data set for grid cells that are populated by less than 10 persons. Hence, we exclude such grids. We also exclude grids with extreme values (lowest and highest 0.1%) in the variables refugee inflow rate, population growth, and growth in available income. The strongest restriction we impose on the sample is that each grid must have housing listings in each year from 2009 to 2017. This leads to an estimation sample of 19,131 grid cells. On the more aggregate level, we distinguish 50 local labor markets in Germany following Kropp and

[3] The IAB GridAB is a project data set compiled as part of the joint research project *Segregation and Regional Mobility* by the Institute for Employment Research (IAB), the Leibniz Institute for Economic Research (RWI), Universitat Pompeu Fabra (UPF) and the Düsseldorf Institute for Competition Economics (DICE).

Figure 1: Administrative Data on Inflow Rate of Refugees



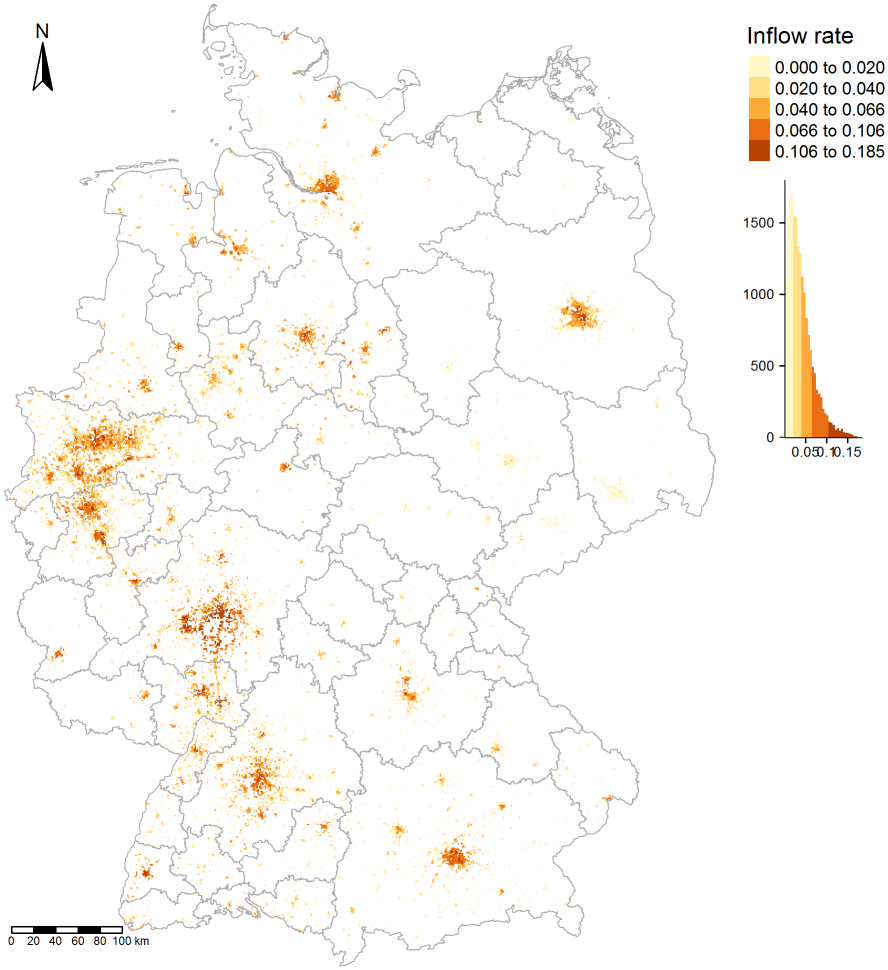
Schwengler (2011). These local labor markets are aggregates of administrative counties that explicitly account for commuter flows.

Inflow Rate of Refugees

We construct our main regressor of interest, the inflow rate of refugees, as the change in the number of residents from typical refugee countries (non-European Islamic and African states) between 2014 and 2017 divided by the overall population in 2014. We use these country groups as the RWI-GEO-GRID does not distinguish the origin by nationality but only by broader language groups. This is because the data provider infers ethnicity from the linguistic origin of fore- and surnames (Breidenbach and Eilers, 2018). Hence, we cannot precisely identify nationality or refugee status. Since we are looking at the net change in the population of non-European Islamic (North African and Middle Eastern) and sub-Saharan origin, we net out German citizens and pre-existing migrants of these origins. To demonstrate that most refugees during this time span were of non-European Islamic or sub-Saharan origin, we separately depict the inflow rate of all refugees and of refugees from Africa and West Asia in Figure 1 using administrative sources. The figure shows that refugee inflows increased strongly starting in 2015, peaked in 2016 when the annual inflow rate amounted to 0.68 percent, and declined rapidly again in 2017. The development of the overall refugee inflow rate coincides closely with that of the subgroup of refugees we are able to proxy for in our data. During the primary years of the refugee crisis, 2015 and 2016, 68.6 percent of all newly arriving refugees originated from Africa and West-Asia. The relative importance of these regions of origin is also reflected in the evolution of the share of African and West Asian refugees among all refugees in Germany, which almost doubled from about 31.8 percent in 2010 to about 60.4 percent in 2017.

Figure 2 shows the geographic distribution of refugee inflows into the 19,131 grid cells included in our sample.

Figure 2: Spatial Distribution of Refugee Inflow Rate



Notes: The figure shows the geographic distribution of the refugee inflow rate between 2014 and 2017 relative to the 2014 population on grid cell level. Grid cells are restricted to those in the estimation sample. Grey lines are the borders of the local labor markets. Additionally, the figure shows a histogram of the distribution of the inflow rate. The bins are based on the method of Fisher-Jenks optimization, which aims to minimize the variance within each bin while maximizing the variance between bins.

Rent Growth

To obtain grid-specific housing values, we run separate hedonic price regressions for sales prices and rents and compute the mean of the resulting residuals. For this, we rely on the listing prices and object characteristics recorded in the RWI-GEO-RED. In the hedonic rent regression, we only include apartment objects as there are only few houses listed for rent. In the sales price regressions, we pool apartments and houses to increase the sample size. The hedonic regressions are estimated separately for each year using the following functional form:

$$p_j = \beta_0 + X_j'\beta_1 + \beta_2 urbanity_{d(j)} + \epsilon_j, \tag{9}$$

Table 1: Summary Statistics

	Sample on Grid-Cell Level				Sample on LLM Level			
	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Outcome Variables								
Population Growth$_{2017}$	0.025	0.042	-0.417	0.881	0.015	0.014	-0.013	0.037
Rent Growth$_{2017}$	0.014	0.126	-1.508	1.471	0.014	0.043	-0.072	0.139
Price Growth$_{2017}$	0.047	0.259	-1.850	3.379	0.043	0.062	-0.104	0.201
Net Income p.c. Growth$_{2017}$	0.061	0.024	-0.127	0.232	0.070	0.012	0.051	0.102
Main Regressors								
Refugee Inflow Rate$_{2017}$	0.038	0.029	0.000	0.185	0.025	0.016	0.002	0.061
Aggregated Inflow Rate$_{2017}$	.	.	.	.	0.016	0.008	0.002	0.040
Migration Model IV	0.035	0.048	0.000	1.180	0.025	0.015	0.003	0.061
Covariates								
Net Income p.c. Growth$_{2014}$	0.073	0.034	-0.165	0.358	0.091	0.017	0.061	0.128
Population Growth$_{2014}$	-0.008	0.047	-0.537	1.350	-0.017	0.014	-0.046	0.018
Share Age Group$_{below15;2014}$	0.133	0.015	0.072	0.203	0.129	0.010	0.109	0.145
Share Age Group$_{above75;2014}$	0.103	0.025	0.023	0.258	0.106	0.010	0.090	0.133
Share Age Group$_{15-25;2014}$	0.110	0.018	0.049	0.247	0.109	0.016	0.073	0.131
Share Age Group$_{26-35;2014}$	0.121	0.029	0.047	0.294	0.121	0.009	0.100	0.146
Share Age Group$_{36-50;2014}$	0.212	0.021	0.115	0.347	0.206	0.009	0.188	0.223
Covariates of Migration Model								
Housing Prices$_{2009}$	-0.006	0.311	-5.294	1.486	-0.095	0.205	-0.473	0.397
Share Refugees$_{2009}$	0.006	0.007	0.000	0.111	0.004	0.002	0.001	0.012
County Level Quota$_{2014}$	0.005	0.008	0.000	0.046	0.020	0.025	0.002	0.111
Observations	19131				50			

Notes: All growth variables correspond to the three year change, i.e. growth rates of 2017 reflect the change between 2017 and 2014. The aggregated inflow rate corresponds to the elasticity weighted average of the grid level refugee inflow rate at LLM level.

where p_j is the log price per square meter, X_j is a set of object characteristics[4], and urbanity is an indicator of the degree of urbanity of the county in which the grid is located. Since all information is self-reported and many items are voluntary, there are many missing values. To address this problem, we follow closely Klick and Schaffner (2021) in their generation of a housing price index and include a separate category for all categorical variables and dummies accounting for the missing information. By retrieving the estimated error term $\widehat{\epsilon}_j$ from the regression and averaging by grid, we obtain the log housing value of the grid cell. From this, we calculate the change in log rents and log house prices by taking the difference of the respective values between 2017 and 2014.

Table 1 provides key summary statistics for our sample of 19,131 grid cells and 50 local labor markets. For the aggregation to the 50 local labor markets, not only the 19,131 grid cells from the estimation sample are used, but all grid cells after removing the outliers as described before (lowest and highest 0.1%). Thus, the aggregation is based on 145,629 grid cells per year. The housing variables at both levels are constructed from

[4]Object characteristics are the number of rooms, categorical variables for the era of construction and equipment, and dummies for first occupancy, balcony, garden, built-in kitchen, guest toilet, basement, and, when looking at sales prices, whether the object is an apartment or house.

the residuals of the same hedonic regression, so that only the average of the residuals at the corresponding level is calculated. The average population growth between 2014 and 2017 was 2.5 percent at the neighborhood level and 1.5 percent at the local labor market (LLM) level. Over the same period, rents increased by 1.4 at both the neighborhood and LLM level, and house prices by 4.7 and 4.3 percent. The average refugee inflow rate was 3.8 percent at the neighborhood and 2.5 percent at the LLM level. There is, however, a lot of variation in local refugee inflow rates, ranging from 0.0 to 18.5 percent at the neighborhood level and from 0.2 to 6.1 percent at the LLM level. The larger increases in population and house prices at the neighborhood level relative to the local labor market level are driven by the fact that, because of our sample selection, the neighborhoods in our sample are located in more densely populated areas.

3.1 First Stage

Since refugee inflows are likely to be endogenous to local conditions, we instrument them following the standard approach in the literature. Altonji and Card (1991) and Card (2001) exploit the fact that immigrants tend to locate in ethnic enclaves upon arrival in their destination countries to construct an instrument. For this, they predict the location of current inflows based on past settlement patterns. We show OLS regression results that capture this location decision at the neighborhood level. Apart from the local enclave regressor, our migration model adds two additional factors: a measure of local housing costs in 2009[5] and refugee allocation quotas at the county level. We use this migration model to predict the inflow of refugees between 2014 and 2017. This is the first step to construct our immigrant shock IV.

Table 2 shows different specifications of this migration model. The dependent variable is defined as

$$\ln(Inflow_j) = \ln\left(\frac{r_{j,2017} - r_{j,2014}}{\sum_j r_{j,2017} - \sum_j r_{j,2014}}\right),$$

where r_j is the number of refugees in the neighborhood and $\sum_j r_{j,2017} - \sum_j r_{j,2014}$ is the observed shock at the national level.

Table 2 reports the estimates of the migration model. The first column shows the univariate regression with only the log population share of refugees in the neighborhood in 2009 as explanatory variable. The statistically significant and positive coefficient confirms the proposed channel of the classical Card instrument. In the specific context of Germany, an important reason why refugees settled into particular locations is due to refugee county quotas. Quotas in Germany follow a two-step procedure where refugees are first allocated to one of the 16 federal states based on the so-called *Königsteiner*

[5] We obtain this measure from hedonic price regressions as explained in Section 3, where 2009 is the earliest available time period for both housing and demographic composition data.

Table 2: Migration Model at Grid Cell Level

	(1) (ln) Inflow	(2) (ln) Inflow	(3) (ln) Inflow
Log Population Share of Refugees in Grid_{2009}	0.848***	0.482***	0.638***
	(0.0313)	(0.0347)	(0.0422)
Log Hedonic Price_{2009}		-0.0382	-0.0207
		(0.199)	(0.194)
Adjusted Log County Refugee Quota_{2014}		0.508***	0.497***
		(0.0411)	(0.0362)
LLM FE	No	LLM	LLM
Weighted	Yes	No	Yes
Adj. R2	0.412	0.403	0.561
Observations	19132	19132	19132

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows regressions for the refugee inflows at the grid level. Inflow is defined as the log of the grid share in the net change of all refugees. Our main explanatory variable is the log past settlement share of refugees. We add local housing costs, refugee allocation quotas, and LLM fixed effects in Columns (2) and (3). Finally, we weight the regression in Column (3) with the grid population in 2014. Robust clustered Standard errors are clustered on LLM level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Schlüssel[6]. Federal states then allocate refugees to their constituent counties[7] based on their own rules. Refugees can generally not move freely during the asylum procedure. For recognized refugees, the federal states regulate residence according to the Integration Act (Integrationsgesetz, 2016). In some states, refugees must reside within the state, in others within the assigned county or municipality. Recognized refugees are free to choose their place of residence when a job or educational program is started. Still, quotas are an important determinant of settlement patterns and, importantly, do generally not vary over time as a function of local conditions. We use the quotas from 2014 collected by Lange and Sommerfeld (2021) and adjust them by the share of the county population that is included in our estimation sample. For example, if only 20 percent of the county population is in our neighborhood sample, we use only 20 percent of the county-level refugee quota. We then used these local quotas as an extra regressor.

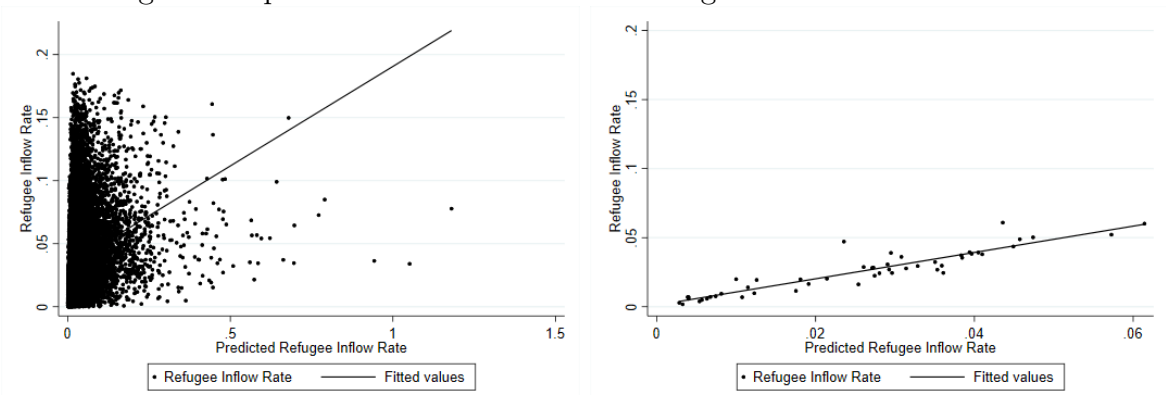
The full migration model also includes local housing costs and fixed effects for local labor markets. Housing prices and labor market fixed effects account flexibly for differences in the baseline level of real wages, which may be important to account for local economies off of the spatial equilibrium (Amior and Manning, 2018) and for the fact that immigrants real wage may assign a different weight to local non-tradables than native workers (Albert and Monras, 2022). The full specification is shown in the third column of Table 2. In each column, we weight observations by the grid level population in 2014.[8]

[6]State-level quotas are determined by tax revenue and population size.

[7]In some cases, federal states allocate refugees directly to individual municipalities.

[8]We repeat the reported regressions with a finer definition of LLMs. This exercise yields similar results, as shown in Table A2. Throughout the paper, we repeat all regressions with the instrument stemming from this specification and including the wider LLM definition. Results stay qualitatively the same and are quantitatively similar.

Figure 3: Spatial Correlation between Refugee Inflow and Instrument



(a) Weighted MM - Grid Cell Level
Slope (se) = .158 (.02)

(b) Weighted MM – LLM Level
Slope (se) = .95 (.042)

Notes: Graphs are scatter plots of the instrument (i. e., the prediction from our migration model in Column (3) of Table 2) on the x-axes and the actual inflow rate of refugees between 2017 and 2014 on the y-axis; solid lines are linear fits. Panel (a) is on grid level, Panel (b) on LLM level. The slope of the linear fit is reported below each graph with its respective standard error. The standard error is clustered on the LLM level on grid level and heteroskedasticity robust on LLM level.

In a second step, we use the predicted values from the weighted migration model to construct the instrument of the refugee inflow rate over the period 2014 to 2017, or, in short, our refugee shock. Since the dependent variable in the migration model is the log share of all refugees that is coming to the neighborhood, we transform the predicted values to match the inflow rate in the following way

$$IV_j = \widehat{Inflow}_j \frac{(\sum r_{j,2017} - \sum r_{j,2014})}{population_{j,2014}}.$$

Additionally, we re-scale this instrument by dividing by its mean and multiplying with the sample mean of the observed inflow rates, such that the means of the instrument and the instrumented variable are the same. Figure 3 shows the strength of the first stage. Equally important for our empirical strategy is to account for potential pre-trends at the local level that are correlated with our instrument, as discussed in more detail below.

4 Main Results

In this section, we present our main results. We start by presenting the estimated impacts of refugee shocks on neighborhoods' populations and rental prices. We then study heterogeneous responses as a function of local housing supply elasticities. Finally, we assess population responses on the local labor market level.

4.1 Estimation Results at the Neighborhood Level

Baseline Estimates

The model introduced in Section 2 shows how we can use regressions of various outcome variables on the refugee inflow rates to test whether refugees have a positive or a negative impact at the local level. In particular, we need to test whether, at the neighborhood level, refugee shocks lead to labor relocation or not.

The main specification in the prior literature to test for systematic local population changes (see e.g. Peri and Sparber, 2011; and Amior, 2020) is the following:

$$\frac{\text{Pop}_{j(c),t+k} - \text{Pop}_{j(c),t}}{Pop_{j(c),t}} = \alpha + \delta_c + \beta \frac{\text{Refugees}_{j(c),t+k}}{\text{Pop}_{j(c),t}} + \varepsilon_{j(c)}, \tag{10}$$

where $\text{Pop}_{j(c),t}$ is the population at time t in neighborhood $j(c)$ in local labor market c, and where $\text{Refugees}_{j(c),t+k}$ represents the inflow of refugees into the neighborhood during the period extending from t to $t+k$. δ_c are local labor market fixed effects that account flexibly for trends at the local labor market level. For the following discussion, it is useful to clarify that the literature usually refers to $\frac{\text{Refugees}_{j(c),t+k}}{\text{Pop}_{j(c),t}}$ as the "refugee shock".

In this regression, β measures the number of new people in the neighborhood per refugee. If everyone of the original population were to remain in the neighborhood, this coefficient would be mechanically equal to 1, since the total population measure includes the refugees themselves. If β is estimated to be larger than one, then the refugee inflow induces some non-refugees to enter the neighborhood (on top of the refugees themselves). In contrast, if the estimate is smaller than one, then the refugee inflow leads to some displacement or crowd-out. A positive estimate of β means that the neighborhood gains population with the refugee inflow, a negative coefficient that the neighborhood loses population on net despite the arrival of the refugees.

Equation 10 is closely linked to Equation 6, the specification implied by the model, which suggests to measure refugee shocks by $\ln(1 + \frac{\text{Refugees}_{j(c),t+k}}{\text{Non-Refugee Pop}_{j(c),t+k}})$. However, when refugee inflows are small relative to the local population and the non-refugee population change is also small, the two measures are almost the same, since for small x we have that $\ln(1+x) \approx x$. In this section, we are consistent with the literature in our specification but we replicate the same results using the model-implied measure of refugee shocks in the Appendix. Both strategies lead to virtually the same point estimates.

Table 3 shows the estimates of the effect of neighborhood-level refugee inflows on population changes. In this table, we do not yet account for any heterogeneity in the data, contrary to what the model suggests, except for the fact that we include local labor market fixed effects interacted with local density.[9] We return to this important

[9] The results with only local labor market fixed effects are similar. We prefer to report this specification because it facilitates comparisons between these estimates and the ones where we interact the refugee shocks with local density.

Table 3: The Effect of Refugee Inflows on Neighborhood-Level Population Changes

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate	0.243***	0.165**	0.426***	0.495***
	(0.0528)	(0.0710)	(0.0587)	(0.134)
Observations	19131	19131	19131	19131
Adjusted R2	0.030	0.044	.	.
AR p-value			0.000	0.000
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate	0.182***	-0.0371	0.298**	0.0869
	(0.0542)	(0.0460)	(0.141)	(0.159)
Observations	19131	19131	19131	19131
Adjusted R2	0.007	0.074	.	.
KP F-Stat.			131.907	33.288
AR p-value			0.042	0.578
MP F-Stat.			125.035	34.208
MP critical value (5 %)			37.418	37.418
Refugee Share 2005			0.385	0.222
St. Error			0.034	0.038
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

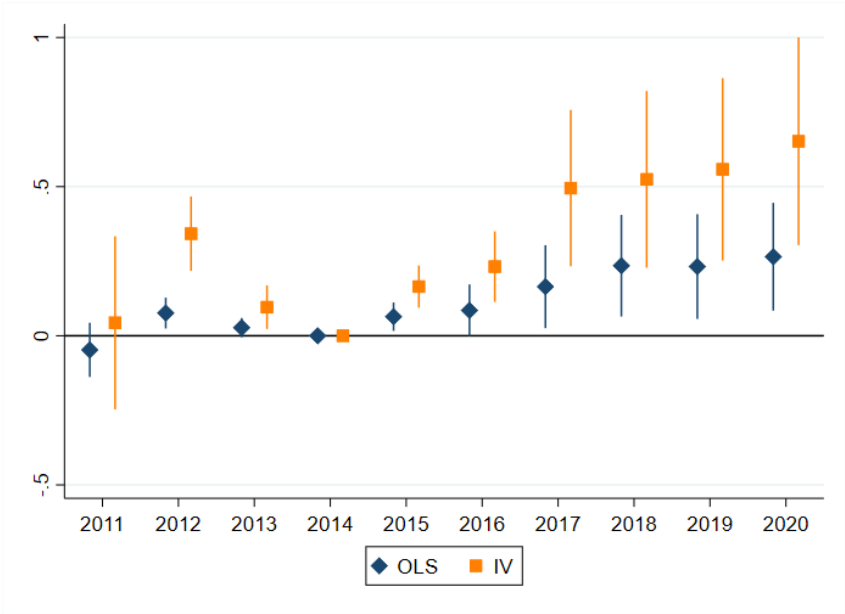
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

point in the next subsection. The OLS estimate in Column (1) of Panel A suggests that for every 10 refugees entering a neighborhood, there is a population increase of about 2.4 individuals. Panel B shows that this estimate is likely to be contaminated by systematic pre-trends. Column (2) shows that our control variables, which include lagged neighborhood-level growth rates of average net income and population (between 2011 and 2014) and lagged neighborhood-level shares of age groups[10] (measured in 2014), do a good job at accounting for these pre-existing trends. The OLS estimate of 0.165 in Column (2) implies that for every 10 refugees entering a neighborhood, the local population increases by 1.7. The estimate in Panel B is close to zero and statistically not significant.

Least square estimates could be biased toward zero, either because the refugee shock is measured with error or because refugees tend to settle in places where population is growing less – something that could occur contemporaneously and hence not necessarily be captured by the pre-trends. Columns (3) and (4) show our IV estimates which should address these two concerns. The point estimate in our preferred specification in Column (4) is around 0.5 and statistically different from both zero and one. This estimate shows that, while refugee shocks lead to more population at the neighborhood level, this increase is clearly less than one for one. The fact that we obtain an estimate different from 0 is a rejection of the hypothesis that refugee shocks do not affect local amenities, as emphasized

[10] Age groups are defined for the population younger than 15 years, from 15 to 25 years, from 26 to 35, from 36 to 50, and older than 75. By leaving out the group from 51 to 75, we are consistent in defining the reference group between the datasets RWI-GEO-GRID and GridAB, as in the latter the sample is restricted to the labor force population and hence, we do not observe children and retirees.

Figure 4: OLS and IV Estimation by Year for Population Changes Relative to 2014



Notes: The figure shows estimated coefficients of the inflow rate with population changes of a longer time span relative to 2014. The inflow rate after 2017 includes the subsequent inflows. All specifications include covariates and density × local labor market fixed effects.

in our discussion in Section 2. Through the lens of the model, the fact that we obtain estimates that are larger than 0, in turn, means that refugees improve the unobserved amenity levels of the neighborhoods they enter.

Our preferred estimate of 0.5 is comparable to others in the literature, although some papers found estimates closer to zero and others obtained results closer to one (see, e.g., Card, 2001; Peri and Sparber, 2011; Amior, 2020; Monras, 2020, 2021; Fernandez-Huertas et al., 2019). None of these previous papers, however, uses the level of granularity that we exploit in this study, with Fernandez-Huertas et al. (2019) coming closest with geographically small Spanish municipalities as their unit of observation.

The model presented above is static, hence, the predictions on mobility should be read as the longer-run outcome. In practice, however, adjustments may occur sluggishly, for instance because of moving costs. In this case, we would expect a lower mobility response in the short run than in the long run, i.e., a larger point estimate on population changes between 2014 and 2015 and a smaller one as we expand the time horizon over which we measure the change in our dependent variable. We investigate whether the results are likely driven by moving costs in Figure 4.[11] As expected, the point estimate increases from 2015 to 2017, and then stabilizes, or slightly increases. Moving costs would generate the opposite pattern, i.e., they would make the estimate move toward zero in the later periods. This suggests that our estimates may be closer to the true long-run estimate, in line with

[11] In the regressions for years beyond 2017, the refugee inflow variable captures as well those inflows that occurred during those additional years.

Table 4: The Effect of Refugee Inflows on Neighborhood-Level Rental Price Changes

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate	0.294**	0.143**	0.389**	0.248
	(0.128)	(0.0586)	(0.158)	(0.162)
Observations	19131	19131	19131	19131
Adjusted R2	-0.001	0.006	.	.
AR p-value			0.019	0.165
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate	-0.0675	0.0267	-0.102	0.0735
	(0.158)	(0.175)	(0.0992)	(0.169)
Observations	19131	19131	19131	19131
Adjusted R2	-0.007	-0.003	.	.
KP F-Stat.			131.907	33.571
AR p-value			0.322	0.662
MP F-Stat.			125.035	34.485
MP critical value (5 %)			37.418	37.418
Refugee Share 2005			0.385	0.222
St. Error			0.034	0.038
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

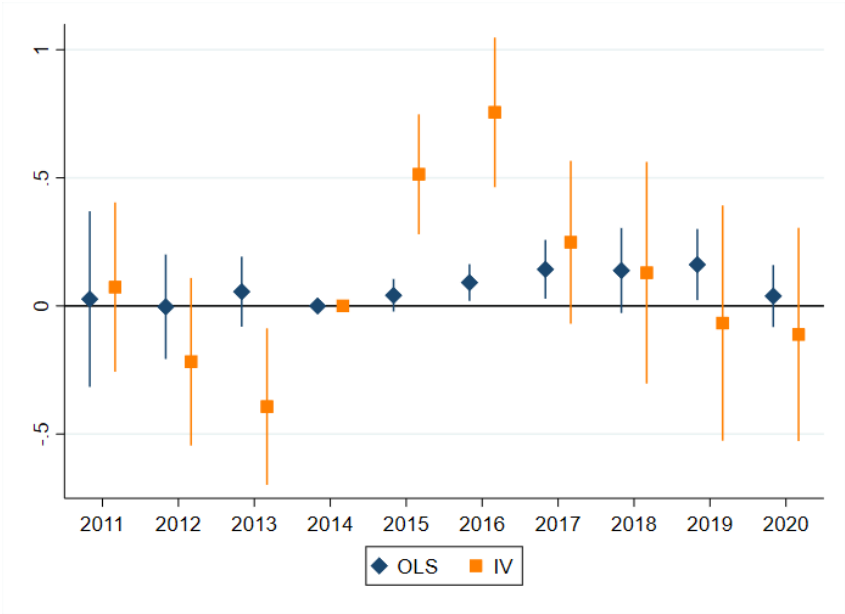
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the fact that, in equilibrium, gross internal migration flows are substantially higher than net flows, and hence, that internal migration adjustments, especially to immigrant shocks (see Blanchard and Katz, 1992; Colas, 2019; Monras, 2020), are relatively quick.

There are two alternative ways to estimate the population response to refugee inflows that are more closely aligned with our model. First, as anticipated previously, the model suggests measuring the refugee inflow as the log of one plus the refugee inflow divided by the non-refugee population. This issue has been discussed in the prior literature (see, e.g., Borjas, 2003; Dustmann et al., 2017; Borjas and Monras, 2017) but in this case it makes little difference as shown in Table A3. Another alternative, consistent with the model, is to use as dependent variable the log change in the share of workers living in each neighborhood, which would follow from Equation 1. Using this alternative dependent variable instead leaves our results virtually unchanged as shown in Tables A4 and A5.

Provided that enough relocation is taking place and that migrants do not affect local amenities, the model predicts that housing prices at the neighborhood level should not be affected by refugee inflows, the intuition being that in spatial equilibrium housing prices only depend on local fundamentals. We present estimates of the impact of refugees on rental prices in Table 4. As before, Columns (1) and (2) provide OLS estimates. In this case, it seems that there are no systematic trends in rental prices prior to the refugee inflow, as shown in Panel B, even without any additional controls. The OLS estimates suggest that refugee inflows lead to modest rental price increases. In Columns (3) and (4), we present our IV estimates. These are similar in magnitude to the OLS estimates but,

Figure 5: OLS and IV Estimation by Year for Rental Price Changes Relative to 2014



Notes: The figure shows estimated coefficients of the inflow rate with rental prices changes of a longer time span relative to 2014. The inflow rate after 2017 includes the subsequent inflows. All specification include covariates and density × local labor market fixed effects.

in Column (4), no longer statistically different from zero. Through the lens of our model, positive estimates indicate that refugee shocks may have had a direct positive influence on neighborhood level amenities, in line with the partial displacement that we estimated in Table 3. According to our model, the ratio of the coefficients reported in Tables 3 and 4 identifies the (average) housing supply elasticity. Using our preferred point estimates in Columns (4), we obtain an elasticity of $\gamma_{j(c)} = 0.495/0.248 - 1 = 1.00$ which lies within the typical range of estimates in the literature (e.g. Saiz, 2010a).

The prior literature reports various point estimates for the response of house prices to immigrant inflows which mostly depend on the geographic aggregation and the time horizon of each particular study. Studies using shorter time horizons tend to report positive and larger point estimates while studies using longer time horizons report smaller estimates, sometimes even negative. Similarly, studies using more geographically disaggregated data tend to find more positive estimates than studies using more aggregate data (see, e.g., the work in Saiz, 2010b; Saiz and Wachter, 2011; Sa, 2015; Monras, 2020). Figure 5 shows that rental prices increased strongly on impact. However, by 2017, they had already adjusted and almost fallen back to their original level (on average). This is yet another indication that adjustment takes place relatively fast.

Local Heterogeneity

The model predicts that, unless refugees affect local amenities, their inflow should not be correlated with population changes. In the previous section, we show that this prediction is clearly rejected by the data. Our findings are consistent with the idea that refugee shocks positively affect local amenities. In this case, the model has sharp predictions on how estimates should vary as a function of the local housing supply elasticity: neighborhoods with less elastic housing supply should experience more displacement and higher rental price increases than neighborhoods with more elastic housing supply.

Knowing the exact housing supply elasticity at the neighborhood level (i.e., by how much housing supply expands given a price increase in housing) is notoriously difficult (Saiz, 2010a). In our context, we flexibly proxy for this elasticity using local population density. To do so, we first construct terciles of population density across all the neighborhoods in our sample. We then interact our measure of refugee shocks, as specified in Equation 10, with dummy variables for each of the three terciles (we report estimates using quartiles and quintiles in Tables A10 and A11 of the Appendix). As shown in Equation 6, we also include interactions between the local labor market fixed effects and the three tercile dummies.

Table 5 shows the resulting estimates by population density group. As predicted when refugee shocks have a direct impact on local amenities, there is a marked (and statistically significant) gradient on how refugee shocks affect local population growth. Both OLS and IV estimates suggest that neighborhoods where housing supply is likely more inelastic experience smaller population growth than neighborhoods where housing supply is more elastic. The IV estimates are, if anything, larger than the OLS estimates, similar to our baseline estimates in Table 3. Panel B of Table 5 shows that there are no systematic pre-trends that could be driving these results.

The evidence presented in Table 5 is again consistent with the idea that refugees have a positive effect on local amenities that manifests itself heterogeneously across neighborhoods as a function of the housing supply elasticity. In this case, the model has an additional prediction, which is that the refugee shock should affect housing prices heterogeneously across neighborhoods, also as a function of the housing supply elasticity.

Table 6 shows the results of the refugee shock on rental prices as a function of our proxy of local housing supply elasticities. As predicted, refugee shocks have a positive and larger effect in more housing-constrained neighborhoods. To recover the housing supply elasticity in each of our three groups of neighborhoods, we can divide the point estimates of each tercile from the population and rental price regressions. Based on the results in Columns (4), the housing supply elasticity in the least dense neighborhoods is around 6.43 ($\gamma_{j(c)} = 0.739/0.0994 - 1 = 6.43$), in medium-dense neighborhoods around 0.197, and in the densest neighborhoods around -0.383 (which we interpret as indicating completely inelastic housing supply in these neighborhoods). Overall, the evidence suggests that refugee inflows have a positive effect on local (unobservable) amenities.

Table 5: The Effect of Refugee Inflows on Neighborhood-Level Population Changes, by Housing Supply Heterogeneity

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate T1	0.395***	0.330***	0.754***	0.739***
	(0.0373)	(0.0506)	(0.115)	(0.151)
Refugee Inflow Rate T2	0.295***	0.229***	0.392***	0.365***
	(0.0211)	(0.0318)	(0.0571)	(0.0961)
Refugee Inflow Rate T3	0.217***	0.127	0.286***	0.287***
	(0.0677)	(0.0868)	(0.0558)	(0.0838)
Observations	19131	19131	19131	19131
Adjusted R2	0.032	0.047	.	.
AR p-value			0.000	0.000
p-Val. T1 vs T3	.01	.01	0	0
p-Val. T2 vs T3	.29	.16	.03	.11
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate T1	0.221***	0.0661	0.383***	0.149
	(0.0586)	(0.0483)	(0.135)	(0.168)
Refugee Inflow Rate T2	0.139***	-0.0119	0.262**	0.0458
	(0.0519)	(0.0414)	(0.119)	(0.152)
Refugee Inflow Rate T3	0.189***	-0.0563	0.282	0.0671
	(0.0597)	(0.0534)	(0.172)	(0.191)
Observations	19131	19131	19131	19131
Adjusted R2	0.007	0.075	.	.
KP F-Stat.			70.690	16.365
AR p-value			0.070	0.694
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2 Estimation Results at the Local Labor Market Level

Amenities are not the only "unobservable" that shapes the attractiveness of a location. It is well known that there are certain characteristics of locations that make them more or less productive. For example, despite large and devastating shocks, Hiroshima and Nagasaki returned to their population trends after the Second World War, as explored in Davis and Weinstein (2002), something that may mean that the (more aggregate) "fundamentals" did not change in those locations despite the enormous shock they suffered during the war.

In this section, and following the model, we investigate whether the immigrant refugee shocks led to changes in population at the local labor market level. For that, we estimate Equation 8. The model once again shows that, unless the refugee shock affects either local amenities or productivity, we should expect a crowd-out of one for one. Given that we follow the literature in using as the dependent variable the population change, this means that we would expect an estimate equal to 0 when regressing population changes on the migrant shocks in local labor markets. A positive number would suggest that immigrants either improve amenities, or productivity, or both.

The results are reported in Table 7. As before, the first two columns show the OLS

Table 6: The Effect of Refugee Inflows on Neighborhood-Level Rental Prices, by Housing Supply Heterogeneity

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate T1	0.0845	0.00595	0.150	0.0994
	(0.100)	(0.0995)	(0.175)	(0.186)
Refugee Inflow Rate T2	0.159*	0.0823	0.331**	0.305**
	(0.0864)	(0.0642)	(0.132)	(0.149)
Refugee Inflow Rate T3	0.344**	0.176**	0.553***	0.465***
	(0.151)	(0.0804)	(0.187)	(0.170)
Observations	19131	19131	19131	19131
Adjusted R2	-0.001	0.006	.	.
AR p-value			0.013	0.030
p-Val. T1 vs T3	.09	.2	.01	.01
p-Val. T2 vs T3	.14	.38	.06	.13
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate T1	-0.0552	0.0512	-0.0491	0.179
	(0.0903)	(0.0982)	(0.190)	(0.238)
Refugee Inflow Rate T2	-0.165**	-0.0635	-0.218*	-0.0171
	(0.0733)	(0.0718)	(0.115)	(0.154)
Refugee Inflow Rate T3	-0.0460	0.0499	-0.0405	0.125
	(0.201)	(0.226)	(0.119)	(0.150)
Observations	19131	19131	19131	19131
Adjusted R2	-0.007	-0.002	.	.
KP F-Stat.			70.690	16.621
AR p-value			0.036	0.214
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

estimates, whereas the last two columns show the IV estimates. The instrument is computed in the same way as on the grid cell level, but using local labor market level data (see Table A1 for the corresponding migration model results). The resulting instrument is shown in Panel (b) of Figure 3. As before, Panel B replicates the structure of Panel A but using the population change between 2011 and 2014, i.e., prior to the refugee inflow shock.

The results show that refugee shocks led to an increase in population of around 3 individuals for every 10 refugees that arrived in the local labor market. This means that there was some relocation but, as before, local labor markets receiving larger inflows ended up expanding. Through the lens of the model, this suggests that refugee shocks are associated with productivity increases, as argued in related work such as Buchardi et al. (2019), Terry et al. (2022), and Peters (2022). Figure A2 in the Appendix shows that the estimates are stable as we expand the time horizon.

Table 7: The Effect of Refugee Inflows on Population Changes on LLM-Level

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate	0.424***	0.142**	0.636***	0.300**
	(0.127)	(0.0619)	(0.140)	(0.147)
Observations	50	50	50	50
Adjusted R2	0.035	0.827	.	.
AR p-value			0.000	0.048
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate	0.248	-0.237	0.657***	0.137
	(0.209)	(0.167)	(0.246)	(0.221)
Observations	50	50	50	50
Adjusted R2	-0.276	0.609	.	.
KP F-Stat.			38.394	7.072
AR p-value			0.004	0.623
MP F-Stat.			60.655	7.110
MP critical value (5 %)			37.418	37.418
Refugee Share 2005			0.950	0.918
St. Error			0.153	0.345
Regional FE	State	State	State	State
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

This paper investigates relocation patterns following the unexpected and large inflow of refugees into Germany during the mid 2010s. We show that the refugee shock increased the amount of workers both at the neighborhood level and at the more aggregate local labor market level, albeit less than one for one. Using a novel multi-geography spatial equilibrium model, we link these estimates to local amenity and productivity changes.

In a next step, we plan to use our reduced-form estimates to back out the structural parameters of the model. With these parameters at hand, we will then investigate whether the refugee shock had a positive or negative impact on the overall German economy. The logic of this exercise follows closely from the insights in Hsieh and Moretti (2019). According to this seminal paper, output in the United States could be higher if labor relocated toward more productive locations which tend to be also more housing-constrained locations. Refugee inflows could (partially) "solve" this labor misallocation, depending on whether they improve amenities in neighborhoods of (initially) more or less productive local labor markets.

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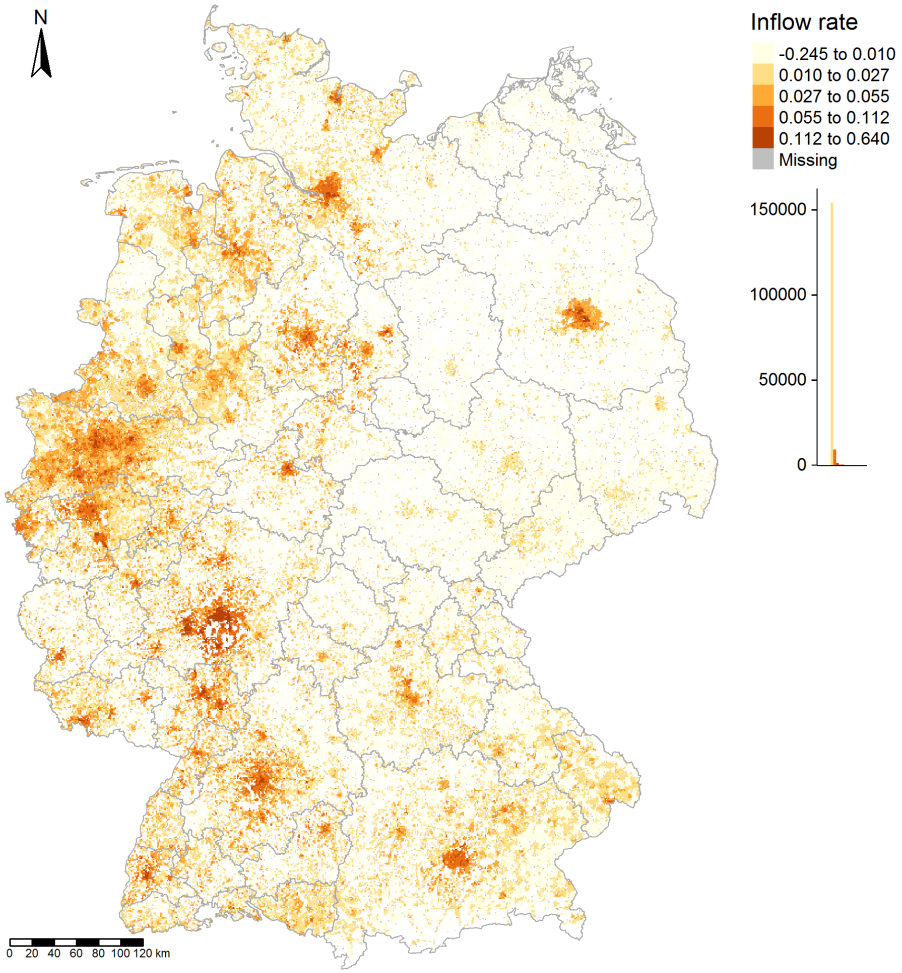
A Appendix

A.1 Data

Figure A1: Spatial Distribution of Refugee Inflow Rate for total Germany



Notes: The figure shows the geographic distribution of the refugee inflow rate between 2017 and 2014 relative to the 2014 population on grid cell level. Grey lines are the borders of the local labor markets. The figure shows additionally a histogram of the distribution of the inflow rate. Bins are based on the method of Fisher-Jenks optimization, which aims to minimize the variance within each bin while maximizing the variance between bins.

A.2 Migration Model

Table A1: Migration Model at LLM Level

	(1) Inflow	(2) Inflow	(3) Inflow
Log Population Share of Refugees in Grid_{2009}	2.412***	0.548**	0.461**
	(0.276)	(0.227)	(0.196)
Log Hedonic Price_{2009}		0.721*	0.691
		(0.421)	(0.420)
Adjusted Log County Refugee Quota_{2014}		0.976***	1.080***
		(0.0837)	(0.0429)
LLM FE	No	State	State
Weighted	Yes	No	Yes
Adj. R2	0.706	0.964	0.982
Observations	50	50	50

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Migration Model with Finer LLM Definition

	(1) Inflow	(2) Inflow	(3) Inflow
Log Population Share of Refugees in Grid_{2009}	0.848***	0.461***	0.618***
	(0.0282)	(0.0230)	(0.0261)
Log Hedonic Price_{2009}		-0.0128	0.0502
		(0.101)	(0.122)
Adjusted Log County Refugee Quota_{2014}		0.543***	0.515***
		(0.0873)	(0.0816)
LLM FE	No	LLM	LLM
Weighted	Yes	No	Yes
Adj. R2	0.412	0.456	0.606
Observations	19132	19132	19132

A.3 Population Estimates at the Neighborhood Level

Table A3: The Effect of Refugee Inflows on Neighborhood-Level Population Changes, Model-implied Measure of Refugee Shocks

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Inflow Rate w.r.t.	0.153***	0.0332	0.406***	0.475***
Non-Refugees	(0.0503)	(0.0629)	(0.0564)	(0.131)
Observations	19131	19131	19131	19131
Adjusted R2	0.009	0.034	.	.
AR p-value			0.000	0.000
Panel B: Placebo (2011-2014)				
Inflow Rate w.r.t.	0.166***	-0.0429	0.284**	0.0834
Non-Refugees	(0.0504)	(0.0411)	(0.134)	(0.153)
Observations	19131	19131	19131	19131
Adjusted R2	0.006	0.075	.	.
KP F-Stat.			146.019	33.858
AR p-value			0.042	0.578
MP F-Stat.			139.403	34.809
MP critical value (5 %)			37.418	37.418
Refugee Share 2005			0.404	0.231
St. Error			0.033	0.040
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: The Effect of Refugee Inflows on Neighborhood-Level Population Changes, Alternative Specification

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate	0.231***	0.158**	0.395***	0.444***
	(0.0509)	(0.0663)	(0.0544)	(0.112)
Observations	19131	19131	19131	19131
Adjusted R2	0.030	0.051	.	.
AR p-value			0.000	0.000
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate	0.173***	-0.00746*	0.277**	-0.0186*
	(0.0531)	(0.00400)	(0.137)	(0.00964)
Observations	19131	19131	19131	19131
Adjusted R2	0.007	0.981	.	.
KP F-Stat.			131.907	33.571
AR p-value			0.050	0.062
MP F-Stat.			125.035	34.485
MP critical value (5 %)			37.418	37.418
Refugee Share 2005			0.385	0.222
St. Error			0.034	0.038
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: The Effect of Refugee Inflows on Neighborhood-Level Population Changes, Alternative Specification using the Model-implied Measure of Refugee Shocks

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Inflow Rate w.r.t.	0.146***	0.0349	0.376***	0.426***
Non-Refugees	(0.0485)	(0.0587)	(0.0519)	(0.109)
Observations	19131	19131	19131	19131
Adjusted R2	0.009	0.041	.	.
AR p-value			0.000	0.000
Panel B: Placebo (2011-2014)				
Inflow Rate w.r.t.	0.159***	-0.00527	0.264**	-0.0179*
Non-Refugees	(0.0493)	(0.00328)	(0.130)	(0.00931)
Observations	19131	19131	19131	19131
Adjusted R2	0.006	0.981	.	.
KP F-Stat.			146.019	34.240
AR p-value			0.050	0.062
MP F-Stat.			139.403	35.192
MP critical value (5 %)			37.418	37.418
Refugee Share 2005			0.404	0.232
St. Error			0.033	0.040
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.4 Rental Price Estimates

Table A6: The Effect of Refugee Inflows on Neighborhood-Level Rental Price Changes, Model-implied Measure of Refugee Shocks

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Inflow Rate w.r.t.	0.281**	0.141**	0.370**	0.238
Non-Refugees	(0.123)	(0.0596)	(0.152)	(0.155)
Observations	19131	19131	19131	19131
Adjusted R2	-0.001	0.006	.	.
AR p-value			0.019	0.165
Panel B: Placebo (2011-2014)				
Inflow Rate w.r.t.	-0.0529	0.0405	-0.0969	0.0705
Non-Refugees	(0.158)	(0.178)	(0.0947)	(0.162)
Observations	19131	19131	19131	19131
Adjusted R2	-0.008	-0.002	.	.
KP F-Stat.			146.019	34.240
AR p-value			0.322	0.662
MP F-Stat.			139.403	35.192
MP critical value (5 %)			37.418	37.418
Refugee Share 2005			0.404	0.232
St. Error			0.033	0.040
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.5 Heterogeneity

A.5.1 Population Estimates

Table A7: The Effect of Refugee Inflows on Neighborhood-Level Population Changes, by Housing Supply Heterogeneity

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate T1	0.410***	0.345***	0.816***	0.777***
	(0.0363)	(0.0485)	(0.152)	(0.172)
Refugee Inflow Rate T2	0.290***	0.227***	0.384***	0.343***
	(0.0276)	(0.0465)	(0.0670)	(0.112)
Refugee Inflow Rate T3	0.283***	0.216***	0.401***	0.363***
	(0.0198)	(0.0260)	(0.0391)	(0.0681)
Refugee Inflow Rate T4	0.211***	0.124	0.254***	0.243***
	(0.0795)	(0.0972)	(0.0650)	(0.0879)
Observations	19131	19131	19131	19131
Adjusted R2	0.027	0.041	.	.
AR p-value			0.000	0.000
p-Val. T1 vs T4	.01	0	0	0
p-Val. T2 vs T4	.28	.17	0	.03
p-Val. T3 vs T4	.42	.29	.02	.01
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate T1	0.166***	0.00942	0.278***	0.00887
	(0.0519)	(0.0480)	(0.0883)	(0.126)
Refugee Inflow Rate T2	0.211***	0.0611	0.300*	0.0726
	(0.0524)	(0.0405)	(0.168)	(0.175)
Refugee Inflow Rate T3	0.142**	-0.0275	0.337**	0.0702
	(0.0639)	(0.0491)	(0.141)	(0.171)
Refugee Inflow Rate T4	0.194***	-0.0585	0.259	0.0216
	(0.0624)	(0.0563)	(0.170)	(0.180)
Observations	19131	19131	19131	19131
Adjusted R2	0.004	0.073	.	.
KP F-Stat.			47.689	16.802
AR p-value			0.010	0.729
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: The Effect of Refugee Inflows on Neighborhood-Level Population Changes, by Housing Supply Heterogeneity

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate T1	0.438***	0.372***	0.862***	0.794***
	(0.0510)	(0.0619)	(0.195)	(0.216)
Refugee Inflow Rate T2	0.360***	0.294***	0.449***	0.379***
	(0.0344)	(0.0446)	(0.0465)	(0.0642)
Refugee Inflow Rate T3	0.271***	0.204***	0.380***	0.312***
	(0.0244)	(0.0392)	(0.0615)	(0.105)
Refugee Inflow Rate T4	0.296***	0.223***	0.400***	0.335***
	(0.0191)	(0.0262)	(0.0332)	(0.0508)
Refugee Inflow Rate T5	0.197**	0.108	0.209**	0.175*
	(0.0907)	(0.106)	(0.0830)	(0.0938)
Observations	19131	19131	19131	19131
Adjusted R2	0.025	0.040	.	.
AR p-value			0.000	0.000
p-Val. T1 vs T5	.01	0	0	0
p-Val. T2 vs T5	.08	.05	.01	0
p-Val. T3 vs T5	.44	.29	0	0
p-Val. T4 vs T5	.31	.22	.05	.03
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate T1	0.168***	0.00625	0.248***	-0.0509
	(0.0563)	(0.0591)	(0.0912)	(0.122)
Refugee Inflow Rate T2	0.230***	0.0746*	0.380**	0.123
	(0.0592)	(0.0404)	(0.166)	(0.182)
Refugee Inflow Rate T3	0.185***	0.0330	0.337***	0.0915
	(0.0564)	(0.0579)	(0.114)	(0.140)
Refugee Inflow Rate T4	0.122*	-0.0592	0.281*	-0.00880
	(0.0660)	(0.0493)	(0.164)	(0.191)
Refugee Inflow Rate T5	0.202***	-0.0488	0.247	-0.00139
	(0.0677)	(0.0608)	(0.175)	(0.184)
Observations	19131	19131	19131	19131
Adjusted R2	0.002	0.070	.	.
KP F-Stat.			44.870	12.695
AR p-value			0.006	0.273
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.5.2 Rental Price Estimates

Table A9: The Effect of Refugee Inflows on Neighborhood-Level Rental Price Changes, by Housing Supply Heterogeneity with Finer LLM Definition

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow	0.138	0.0737	0.284	0.208
Rate T1	(0.103)	(0.113)	(0.241)	(0.281)
Refugee Inflow	0.178*	0.114	0.406***	0.357**
Rate T2	(0.0954)	(0.0833)	(0.151)	(0.168)
Refugee Inflow	0.275**	0.130	0.317**	0.299*
Rate T3	(0.129)	(0.0898)	(0.158)	(0.154)
Observations	19131	19131	19131	19131
Adjusted R2	-0.035	-0.031	.	.
AR p-value			0.004	0.126
p-Val. T1 vs T3	.36	.68	.89	.71
p-Val. T2 vs T3	.39	.88	.65	.72
Panel B: Placebo (2011-2014)				
Refugee Inflow	-0.114	0.0177	-0.148	-0.0323
Rate T1	(0.0991)	(0.119)	(0.229)	(0.327)
Refugee Inflow	-0.184**	-0.0599	-0.250	-0.171
Rate T2	(0.0805)	(0.0923)	(0.154)	(0.265)
Refugee Inflow	-0.0152	0.109	-0.209	-0.157
Rate T3	(0.184)	(0.208)	(0.165)	(0.236)
Observations	19131	19131	19131	19131
Adjusted R2	-0.039	-0.035	.	.
KP F-Stat.			17.673	14.183
AR p-value			0.275	0.789
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: The Effect of Refugee Inflows on Neighborhood-Level Rental Price Changes, by Housing Supply Heterogeneity

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow	0.108	0.0363	0.265	0.280
Rate T1	(0.106)	(0.103)	(0.263)	(0.266)
Refugee Inflow	0.134	0.0563	0.169	0.187*
Rate T2	(0.112)	(0.0846)	(0.110)	(0.0972)
Refugee Inflow	0.127	0.0328	0.297**	0.297*
Rate T3	(0.0841)	(0.0480)	(0.142)	(0.171)
Refugee Inflow	0.371**	0.206**	0.685***	0.642***
Rate T4	(0.150)	(0.0828)	(0.182)	(0.181)
Observations	19131	19131	19131	19131
Adjusted R2	-0.004	0.003	.	.
AR p-value			0.025	0.009
p-Val. T1 vs T4	.06	.15	.04	.07
p-Val. T2 vs T4	.05	.16	0	0
p-Val. T3 vs T4	.02	.06	0	0
Panel B: Placebo (2011-2014)				
Refugee Inflow	-0.0812	0.0182	-0.0303	0.175
Rate T1	(0.101)	(0.103)	(0.221)	(0.233)
Refugee Inflow	-0.136	-0.0263	-0.132	0.0562
Rate T2	(0.0934)	(0.0997)	(0.173)	(0.208)
Refugee Inflow	-0.143*	-0.0411	-0.199**	-0.0162
Rate T3	(0.0756)	(0.0810)	(0.0926)	(0.115)
Refugee Inflow	-0.00836	0.0829	-0.0381	0.102
Rate T4	(0.222)	(0.245)	(0.129)	(0.142)
Observations	19131	19131	19131	19131
Adjusted R2	-0.010	-0.006	.	.
KP F-Stat.			47.689	16.965
AR p-value			0.135	0.435
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

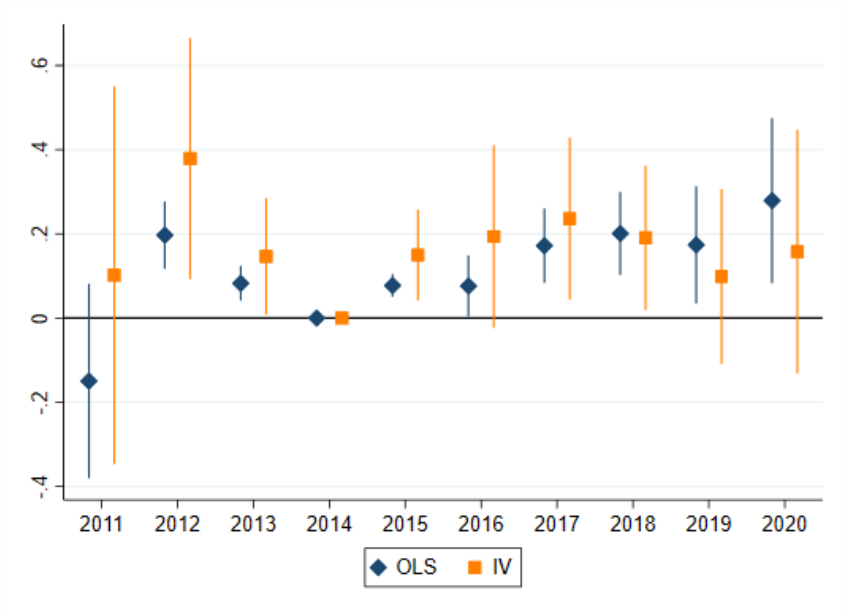
Table A11: The Effect of Refugee Inflows on Neighborhood-Level Rental Price Changes, by Housing Supply Heterogeneity

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Change from 2014 to 2017				
Refugee Inflow Rate T1	0.133	0.0652	0.502*	0.478*
	(0.123)	(0.123)	(0.257)	(0.264)
Refugee Inflow Rate T2	0.0910	0.00986	-0.0169	-0.0492
	(0.118)	(0.0872)	(0.161)	(0.128)
Refugee Inflow Rate T3	0.126	0.0485	0.392***	0.368**
	(0.111)	(0.105)	(0.147)	(0.181)
Refugee Inflow Rate T4	0.165	0.0603	0.343**	0.285**
	(0.102)	(0.0570)	(0.160)	(0.135)
Refugee Inflow Rate T5	0.387**	0.222**	0.639***	0.565***
	(0.151)	(0.0879)	(0.179)	(0.189)
Observations	19131	19131	19131	19131
Adjusted R2	-0.006	-0.000	.	.
AR p-value			0.038	0.046
p-Val. T1 vs T5	.07	.24	.53	.68
p-Val. T2 vs T5	.01	.04	0	0
p-Val. T3 vs T5	.12	.26	.1	.17
p-Val. T4 vs T5	.02	.05	.02	.01
Panel B: Placebo (2011-2014)				
Refugee Inflow Rate T1	-0.169*	-0.0654	-0.214	0.0382
	(0.0996)	(0.0962)	(0.240)	(0.238)
Refugee Inflow Rate T2	0.000160	0.110	0.0326	0.264
	(0.0988)	(0.110)	(0.177)	(0.226)
Refugee Inflow Rate T3	-0.163**	-0.0541	-0.175	0.0547
	(0.0823)	(0.0816)	(0.134)	(0.146)
Refugee Inflow Rate T4	-0.199**	-0.102	-0.226*	0.00498
	(0.0793)	(0.0944)	(0.130)	(0.166)
Refugee Inflow Rate T5	0.0200	0.111	0.0498	0.221
	(0.244)	(0.267)	(0.197)	(0.192)
Observations	19131	19131	19131	19131
Adjusted R2	-0.012	-0.008	.	.
KP F-Stat.			44.870	12.737
AR p-value			0.104	0.341
Regional FE	LLM x Density	LLM x Density	LLM x Density	LLM x Density
Covariates	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.6 Aggregated Shock

Figure A2: OLS and IV Estimation by Year for Population Changes Relative to 2014 on LLM Level



Notes: The figure shows estimated coefficients of the inflow rate with population changes of a longer time span relative to 2014. The inflow rate after 2017 includes the subsequent inflows. All specification include covariates and state fixed effects.