IMMIGRATION AND THE HOUSING MARKET:

THE GERMAN CASE

Mourad Alkalza

ID:10196000

Under the supervision of:

Dr Mazhar Waseem

Abstract

In 2015 Germany experienced the largest influx in immigrants the EU has seen in years, increasing the percentage of immigrants in Germany to over 12%. This was bound to affect the German economy. During that period, Germany also experienced a rise in price changes. Given that, I set to study the effect of immigrants on the German housing market over 387 different government districts between the periods of 2012 and 2018. I use a fixed-effects "Within" model to account for any district and time fixed-effects, in addition, I make use of the share-shift methodology. And as a result, I find a positive correlation between the level of immigrants and both house and flat rents and prices, where a 1% increase in the number of immigrants relative to the population results in an increase by 0.59% to 1.19% prices and rents across all types of dwellings. The results of this paper may be used for further research into the study of immigration and markets.

Keywords

Immigration, Housing Market, Germany

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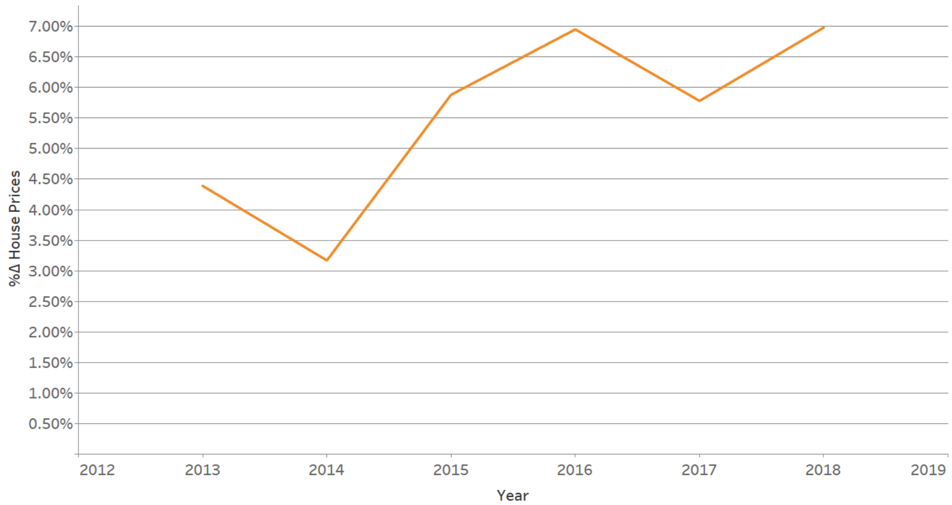
1 Introduction

The main concept of the paper is to study and analyses the effect of immigrants from 2012 to 2018 on the prices/rent rate of houses and flats within German regional districts. It will be using panel data from 2012 to 2018 and will make use of a share-shift IV estimator to account for the non-randomness nature of the immigrant independent variable. What the results found was a positive correlation between immigrants and house/flat prices/rents, which will be looked into deeper throughout this paper.

The topic of immigration in Europe has been hot and controversial in the last few years. As turmoil and war spread in the Middle East, and especially Syria, European countries were faced by a large influx of immigrants, which has caused a lot of controversy around decisions of letting immigrants in. Out of all the European countries Germany has been the largest receiver of immigrants, in absolute terms, this was bound to cause social and economic discourse. Although Germany is economically stable and is large enough to withstand this large inflow of migrants, this hasn't stopped citizens of Germany from opposing the decisions, with several anti-immigration protests in late 2014 and summer of 2015. With the 2015 Paris terrorist attack Germany immediately acted and reintroduced border controls at higher rates followed by many EU states doing the same, all to reduce the flow of immigrants, asylum seekers and illegal migrants.

In order to further motivate this topic, I make use of some simple data. I begin by plotting the change in house prices and the change in the number of immigrants over the period of 2012-2018, found in Figure 1 and 2. We can see that the rise of immigrants flowed by a rise in the percentage change in the house prices until 2015, where the number of inflow immigrants' peaks, the percentage change in house prices continues to rise. This might suggest that the effect of immigrants might continue to several years after.



To look deeper into this data, we refer to figure 2 which visualises the change in both immigrants to population ratio (left) and house prices (right) on a map of Germany. When looking at immigrants we can see that the level of immigrants has mostly increased in the south and west of Germany, including Berlin. We can then see some similarities between both maps, with house prices, in addition to Berlin, some in the west and especially the south, in the state of Bayern, experienced a large increase at the same period.

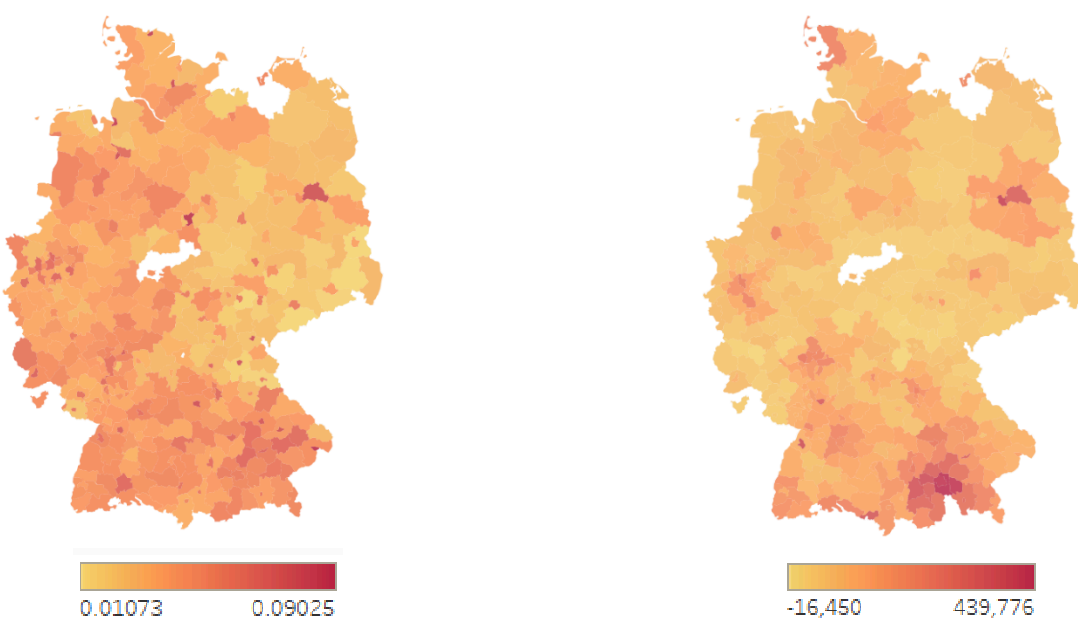


Figure 3: The left shows the change in the ratio of immigrants to the population from 2012 to 2018. The right shows the change in house prices from 2012 to 2018. The redder the area is the larger the change between the years

Note: there are a few districts that are missing due to data being unavailable

It's important to notice that house prices can fluctuate based on many factors if the supply of housing properties doesn't catch up with the demand of prices will likely to increase this is exactly what was happening in Germany in 2018 (G P G N T, 2018). Although this data might not be seen as proof that there is a correlation between the two variables, it still shines light around the idea that there might be some sort of correlation between immigration and house prices.

2 Literature review

Immigration and its effects are a well-studied field in economics especially in the 21st century where the implications of immigration have been growing. In terms of markets that were studied, The labour market which has been thoroughly studied has great importance and impact within this study, (Dustmann, Frattini and Prestion, 2011**)** found that areas with large immigrant population density relative to native population density experience a decrease in wages, whereas areas with low immigrant population density relative to native population density experience increased wages. This finding goes in conjunction with the findings of (Aldashev et. al, 2018) where they found that there is a substantial gap in wages between immigrants and natives for observationally similar characteristics, this suggests that immigrants suppress wages as a result of the wage gap. This finding opposes other findings like (Card, 1990) which found a significantly small effect off immigration of Cubans on wages of non- Cubans in Miami. given that our model is simply a supply and demand case, studies like these are vital for understanding the mechanism of the housing market. As factors like unemployment, wages and wealth play an important role in defining prices and inflation. For example, higher wages might result in higher disposable income, resulting in higher wealth which in turn pushes prices up including prices of residential properties.

When looking at literature that studied the effect of immigration on housing markets, a clear separation in results is found. Studies like (Saiz, 2007) that looked at the effects of immigration in major cities in the US between 1983 to 1997, and by incorporating the “Share-shift” IV that dealt with the endogeneity problem, found a positive correlation between immigration inflow and house rent prices. Where an increase of 1% in immigrants resulted in approximately a 1% increase in rent and housing values. Other studies like (Degen and Fischer, 2017) found that immigrants are most likely to rent than buy houses, making it consistent with the findings of (Aldashev et. Al, 2008) as immigrants tend to be on the lower end of the wage distribution thus opting for the cheaper option, which in their case causes multi-family house prices to increase. They've also found that immigration inflow of 1% of an area's population is followed by an increase in prices for single-family homes of about 2.7%. (Muller, 2018) and (Gonzalez and Ortega, 2009) also found positive correlations in both Sweden and Spain respectively**,** where (Gonzalez and Ortega, 2009) also found that immigrants account for 37% of the total constructed residential housing, this suggests that immigrants have a great impact on the supply of housing.

On the other hand, studies like (Sá. 2011) found that an inflow of immigrants of 1% of the local UK population reduces local house prices by 1.6%. A study that is slightly different from the rest of the literature is the paper done by (Rauck and Kvasnicka, 2018), where they look at the effects of refugees on the housing market in Germany right before and after the refugee crisis in 2015, by looking at the allocation of refugees and surprisingly it found a negative correlation, which goes against previous literature, this can be a result if refugees being different to economic migrants as they are housed differently and usually relocated within 3 months.

When looking at the literature there isn't a clear census over the effect of immigration on the housing market, especially with the case of Germany, where there hasn't been a study looking at the effect of immigration at that time period of 2012 to 2018 only one paper (Rauck and Kvasnicka, 2018) (to my knowledge) has looked at a similar topic, yet the effect of immigrants is different to the effect of asylum seekers, given the nature of their financial status and the reasons to travel. So, I believe that my study will be able to introduce a new perspective to the field. Also, the incorporation of interest rates hasn't been done before in this field of study (as far as I know). also given that the data source Empirica Systeme is fairly new, it is difficult that any study before has used this data, so I believe that I'll be the first to use this set of data.

3 Methodology

3.1 Fixed-effects Model

The intuitive and thermotical part of the model is borrowed from (Saiz, 2007) which was later updated by (Sá, 2015) to account for income effects and natives' preferences to immigrants. Where they outline a simple supply and demand equilibrium problem of the housing market. The model assumes that natives are exogenous, and immigrants are endogenous, meaning natives can be either high-income earners or low-income earners, whereas immigrants are only low-income earners (Aldashev et. Al, 2008). This categorization of the population helps with including the labour market aspect of the model, by including the income of different types of people, it can measure how net migration within regions affect total wealth.

To better explain this, we can theorise that if immigrant inflow is offset by native outflow, due to natives have a distaste to immigrants, then there will still be an effect on wealth thus housing prices will be affected, given that the wages of immigrants are not the same as wealthy natives then overall wealth will likely decrease. Even if natives prefer immigrants and decide not to migrate, average wealth will decrease but overall wealth will rise.

The Proposed model has been inspired (Sá, 2015), (Saiz, 2007) and (Muller, 2018)

$$ln\left(p_{xit}\right) = \alpha + \beta\frac{immigrants_{it}}{population_{it-1}} + \gamma_1 unemployment\ rate_{it-1} + \gamma_2 GDP\ per\ Capita_{it-1} + \gamma_i + \mu_{it}$$

(1)

Where $log\left(p_{xit}\right)$ is the natural log prices in region (*i*) at time (*t*), where subscript (*x*) dictates if it is one of four types of prices, either house and apartment prices or house and apartment rental rate. α is a constant and γi is the unobserved heterogeneity term. $\frac{immigrants_{it}}{population_{it-1}}$ is the main independent variable of interest, it calculates the number of immigrants relative to the total population in region (*i*) at time (*t*). and the coefficient β is the percentage change in house/apartment prices/rents as a result of a change of 1% of immigrants relative to the population of the region (Saiz, 2007). The rest of the variables measure the unemployment rate and the disposable income in region (*i*) at time (*t*).

Based on the fact that the data used in modelling is panel data spanning from 2012 to 2018, I'll be estimating this model in two methods, first with an Ordinary least square estimator. With OLS I am well aware that it is not the most efficient method and that it could return biased estimators based on the fact that the unobserved heterogeneity term will remain in the model. However, the inclusion of an OLS estimator would help with comparisons between the other models.

Second, using a fixed-effects within estimator with a two-ways effect, which does a region and time fixed-effects. FE allows me to remove any unobserved heterogeneity over regions and throughout time. I divert slightly from (Sá, 2015), (Saiz, 2007) and (Muller, 2018) where they use a first-difference, I use a within estimator, its important to note that both achieve the same goal, however with first-difference a full year of observations is lost, which is the motivation behind using a within estimator.

The use of time series estimation, as in ARIMA, is possible but based on the nature of the data being limited, the ARIMA estimate might not be accurate. Also, using it might result in the loss of many observations.

Following (Muller, 2018) I estimate the same model, however, I lag the controls once again, as seen in equation (2), this is to tackle the potential correlation between the district trends from the controls and the level of immigrants.

$$ln\left(p_{xit}\right) = \alpha + \beta\frac{immigrants_{it}}{population_{it-1}} + \gamma_1 unemployment\ rate_{it-2} + \gamma_2 GDP\ per\ Capita_{it-2} + \gamma_i + \mu_{it}$$

(2)

The coefficients are the same as the ones in equation (1). The larger distance between the control variables and the dependent variable might result in less reliable results, so both specifications will be considered in the results section.

(Jacobsen, 2005) found that the main four drivers of house prices are interest rates, number of dwellings constructed, unemployment and disposable income. In the above model, I have included two of those drivers. The number of constructed dwellings hasn't been added due to the inability to find the data, this might restrict the results because the presence of a variable measuring the number of dwellings will allow the model to take in account the supply side of the market, given the demand side has already been taken into consideration by including the population and disposable income. Concerning the interest rates variable, it is not included because the inclusion of it is unnecessary as it is a constant term throughout different regions and will be removed due to using a fixed-effects model.

However, the importance of interest rates is not ignored, it is clear that interest rates affect the desirability of buying houses. As interest rates rise potential mortgage owners might change their mind and opt for a cheaper alternative by renting, and the opposite is true when interest rates are reduced potential mortgage owners might decide to buy houses as it becomes the more affordable option.

3.2 IV Model

One reason that might cause this model to have inaccurate causality between the independent and dependent variables is the nature of how the independent variable (immigrants) is assigned. Immigrants aren't randomly allocated, they would usually choose to live in areas with a specific feature, for example, immigrants might prefer to locate in areas with high economic activity in order to have better opportunities. While others might want to locate in an area where economic activity is slow, as prices would generally be lower. However, there is another pull factor affecting the immigrant levels in a specific area, which is the presence of people with similar backgrounds (nationality). A study that was done by (Bartel, 1989) that although was conducted in the US, found that immigrants tend to locate in areas where the level of immigrants is already high.

So, in order to solve this, I will be using a 'shift-share' IV estimator, originally presented by (Bartik, 1991) but famously developed and used by (Card, 2001) and (Saiz, 2003) to solve a similar problem. This IV will result in a more consistent result, as any bias will be accounted for. But before explaining the model an important problem needs to be addressed. For this study, data on characteristics of the origin country are needed further on, however many countries have limited data, e.g. Syria which is an important contributor to the level of immigration in Germany and the EU. So, to avoid excluding any country, I'll be clustering countries into 18 groups, based on their geographical location and their income levels, e.g. Middle Eastern countries with high income would be one group. However, this approach might cause some noticeable noise.

$$V_{i,t} = \sum_{c} \frac{foregin\, pop_{c,i,t_{2011}}}{foregin\, pop_{c,t_{2011}}} \cdot \hat{immigrants}_{c,t} \quad for\, t_{2011} < t \qquad (3)$$

Equation (3) shows how the share-shift IV will work. $\frac{foreign\, pop_{c,i,t_b}}{foregin\, pop_{c,t_b}}$ is the share-shift ratio of foreign-born from cluster (*c*) in region (*i*) at base year (t_{2011}) form the total population of foreigners from cluster (*c*) at base year (t_b), it is one of the determining factors for immigrants when they decide on where to locate, To put it simply the ratio measures the network of a specific group of immigrants in a specific district. This ratio is then multiplied by $\hat{immigrants}_{c,t}$, which is the number of total immigrants from cluster (*c*) at time (*t*). The base year is decided to be 2011, this is not the ideal option for a base year, however, it was chosen because German data collection methods, in terms of the geography of different districts, has changed, so data on some districts are not available before 2011. A base year further from the dataset time period is preferred.

By doing so, I'll be able to estimate the number of immigrants from cluster (*c*) at time (*t*) in region (*i*), and by calculating the sum of those, I'll be able to get estimates of the number of immigrants in region (*i*) at time (*t*).

Before instrumenting $V_{i,t}$ there is a shortcoming that needs to be addressed. To keep this IV valid, I'll have to follow two assumptions that Saiz (2007) have set. The first assumption is that immigration in the base year is not motivated by any omitted variables that might affect the housing market prices. The second assumption is that there is a possibility that changes in national immigration flows are endogenous to the economic condition or house prices in the immigrant destination. The second assumption can be relaxed, to do that I'll be using a similar method that Muller (2018) used to tackle the same problem, given that both papers assess countries in the EU and during the same time period, meaning push factors might be similar. The idea is to regress the number of immigrants from cluster (*c*) on several explanatory variables, which will look like this.

$$\hat{immigrants}_{c,t} = \alpha + \beta_1 GDPpercapita_{c,t} + \beta_2 infant\,mortality + \beta_3 population +$$

(4)

Where $\hat{immigrants}_{c,t}$ is the number of immigrants in Germany from cluster (*c*) in year (*t*). And α is a constant. The independent variables are GDP per capita, infant mortality, the population in cluster (*c*) and deaths in battle in cluster (*c*) in year (*t*). γ_c is the clusters' fixed-effects, $\mu_{c,t}$ is the unobserved error term. By estimating the level of immigrants using these variables, I’ll be able to capture any push factors that affect the decision to immigrate.

4.Data

4.1 Data Sources and Variables

The data used in the modelling is extracted from 3 main sources, 2 of which are German-based. Details of each variable and their sources are in the Appendix in Table 11. The data spans from the years 2012 to 2018 and is observed yearly on the government district level. Originally there are 401 districts in Germany but due to a mix of geographical changes and missing data, as a result, I'll be using only 387 for both the fixed-effects and IV models.

The dependant variable of interest is a group of values measuring the prices in the housing market within Germany. To be more precise I will be estimating the same model but for; flat rents, flat prices, house rents and house prices. This allows to study the market in a more in-depth manner rather than getting an average of the whole market. This can be followed by the fact that immigrant demand of dwellings, similar to any other group of people, is not constant throughout all types of dwellings, and are more likely to choose the smaller or cheaper option. The data is available from 2012 to 2019, which is one of the reasons the study starts from the year 2012.

The main explanatory variable is the level of immigrants, it simply measures the number of foreign-born persons without a German passport in an area at a given time. It spans from the year 2011 to 2018. As mentioned before, in order to address the potential problem of non-randomness of the immigrants I estimate the levels of immigrants using historic ratios of immigrants in 2011 in each district, this proposes a possible bias problem as immigrants would be allocated based on the location of people similar to them.

Other control variables include the disposable income in each district and the unemployment rate on all income levels. The inclusion of more controls is favourable. Other variables should have been included in the specification that could help with increasing the accuracy of the estimation, (Jud et al, 1996) and (Glaeser and Shapiro, 2001) discuss the importance of unemployment, income and education on house prices. In addition, based on (Saiz, 2007) the demand for housing affects prices, and so a variable measuring the number of dwelling could have been effective if included in the model. But due to data limitation, those variables are not included in the model.

Variables regarding the estimation of immigrants from each country for the IV are gathered from the World Bank database. It includes push factors that might motivate immigration, variables include; GDP, population levels, battle deaths and infant mortality rate. These variables are for all available countries, however, due to missing data on several countries due to war or generally bad statistical offices, I cluster the countries into 18 different groups based on both similar geography and income levels.

4.2 Descriptive Statistics

Table 1 shows the descriptive statistics of the raw data, I provide this to give a clear picture of the data. From looking at the data we can see that the standard deviation is slightly large for the main dependent variables, in addition, the main explanatory variable also has a large standard deviation, this might suggest heterogeneous data, which is confirmed after conducting a Breusch-Pagan test.

Table 1: Descriptive statistics

Variables	N	(1) Mean	(2) St. Dev.	(3) Min	(4) Max
Flat Rent €	2,709	491.8	134.0	260.7	1,274.0
Flat price €	2,709	161,780.7	77,971.4	36,756.2	706,461.2
House rent €	2,709	972.5	317.1	419.6	2,694.8
House price €	2,709	303,380.0	180,233.1	68,327.8	1,634,153.0
Immigrants	2,709	23,338.6	46,911.4	524	888,555
Population t-1	2,709	206,304.7	241,366.4	34,011	3,613,495
Disposable income € t-1	2,709	4,321,210.0	5,017,573.0	624,347	73,067,596
Unemployment rate t-1	2,709	6.0	2.9	1.2	16.7
Disposable income € t-2	2,709	4,209,320.0	4,872,346.0	621,551	69,310,763
Unemployment t-2	2,709	6.3	3.0	1	17

To better visualise the data, I separate the data into districts with high and low immigration, I then regress the prices on district dummies, afterwards a calculate the residuals which are then averaged for each year and separated by each type of dwelling. Figure 3 and 4 show the plotting of the residuals. In both graphs areas with high immigration levels, denoted by (H), started with a lower level of residuals than the low immigrant counterpart, denoted by (L), during 2014 to 2016 prices in districts with high levels of immigrants experienced a jump in residuals and by 2018 surpassed their counterparts. This could suggest that there is indeed a correlation between both levels of immigrants and that the large flow of immigrants in 2015 did indeed push prices up.

Other Descriptive statistics for the; share-shift ratios, the IV data and the immigration estimation data can be found in the appendix under Tables

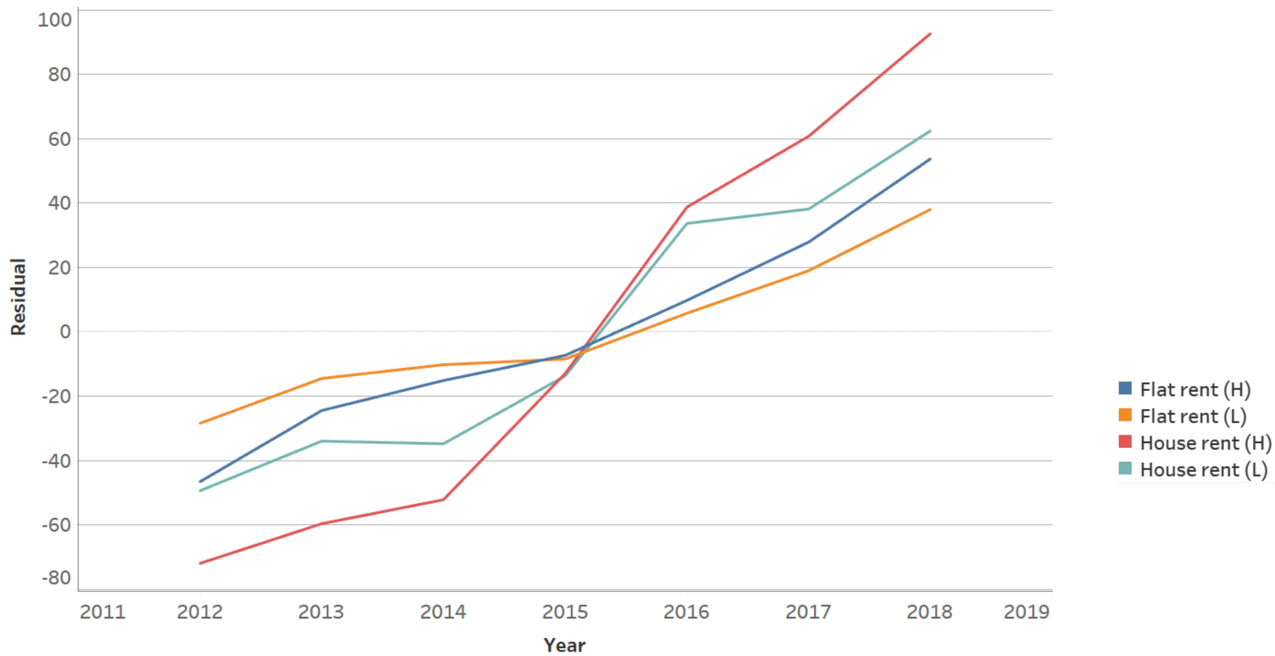


Figure 4: Plots the residuals of each type of dwelling rents from 2012 through 2018
(H) denotes high immigrants and (L) denotes low immigrants
This means that Flat rent (H) refers to the residuals of flat rents in districts with high levels of immigrants

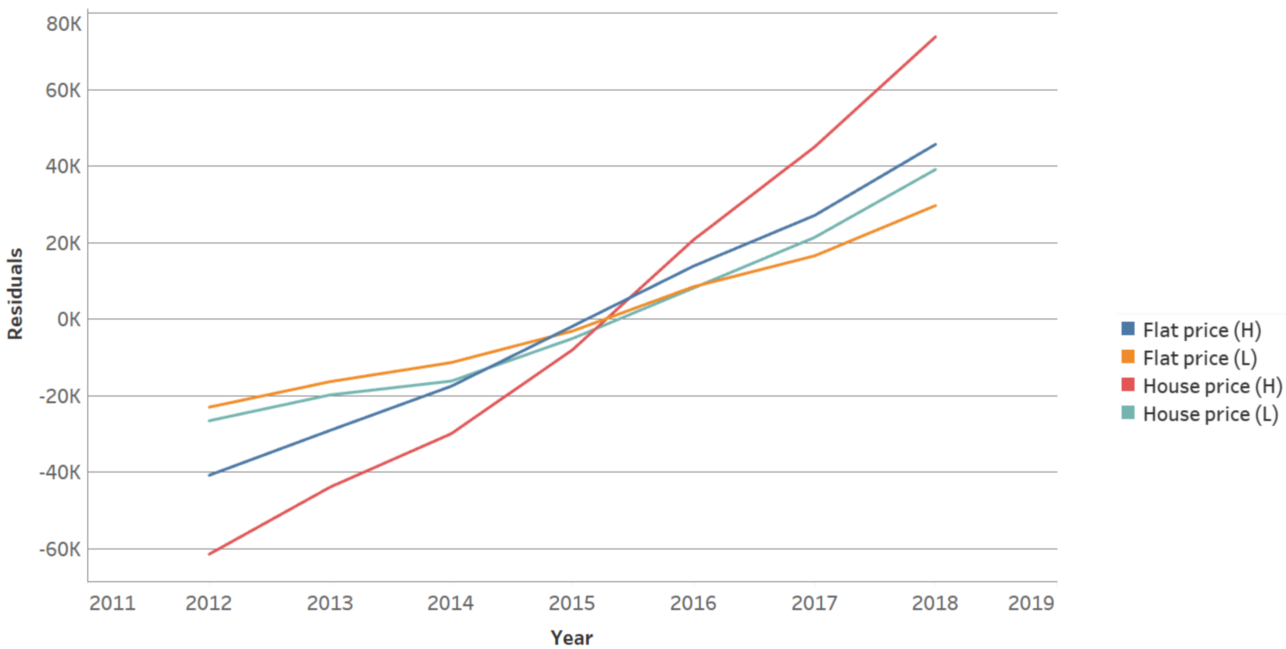


Figure 5: Plots the residuals of each type of dwelling prices from 2012 through 2018
(H) denotes high immigrants and (L) denotes low immigrants
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5 Results

5.1 Fixed-effects Results

The results for the fixed-effects model can be found in Table 2, there are 8 equations that are separated by different categories. Equations 1 to 4 refer to log of flat rents and prices, while equations 5 to 8 refer to log of house rents and prices, and equation 2,4,6 and 8 are the same as equations 1,3,5 and 7 respectively but have control variables that are lagged twice rather than once. It's also important to note that all equations include both district and year fixed effects. The main focus is the equations of the controls that are lagged once. The separation of the prices is vital as it allows to see the effect of immigrants on a much deeper level.

From looking at the data we can see that a 1% increase in immigrant population affects prices by 0.59% to 1.19% when including controls with one lag. However, when we consider the equations with a second lag, we see that the effect is larger, where a 1% increase in immigrants increases prices between 0.65% and 1.37%. this could be supported by the notion that markets usually take time to adjust to any external shock, such as a sudden increase in population. The results also suggest that flat prices are the most sensitive to changes in levels of immigrants while flat rents are less sensitive, this goes against what (OECD/European Union, 2015) and (Degen and Fischer, 2017) found, which is that immigrants lean more toward renting than buying dwellings, however, House prices and rents do follow this notion as rents are more sensitive to change than prices.

Coefficients of unemployment rates are generally positive meaning higher levels of immigrants increase unemployment; this might suggest that immigrants are “freeloading” which is a statement used by many anti-immigrant groups. However, the level of immigrants includes people outside the labour force, which makes the coefficient of unemployment less useful

The motivation for including robust standard errors in both models rises from the fact that both the Breusch-Pagan and Breusch-Godfrey were conducted and both heteroskedasticity and serial correlation were present in all models, and so standard errors were provided using the Arellano method to tackle both problems.

5.2 IV Results

Next, we look at the results that were produced by the IV estimation in Table 3, the structure of the table is the same as Table 2. The results seem to be quite different compared to the FE results, for both house rents and prices the main coefficients are much smaller than before, ranging from 0.063 to 0.185. And when looking at flat rents and prices we find negative coefficients ranging from -0.49 to -0.15. In addition, all coefficients of the main explanatory variable except the ones for flat rents are insignificant. This is no surprise here, as poorly specified IV estimators tend to raise the standard errors which were suggested by (Muller, 2018) and (Nelson and Startz, 1988). We can further back this up by addressing two issues with the IV. First, the use of clustering of countries into only 18 groups does not help capture the true network of those group. Second, the use a base year (for the share-shift) that is very close to the study’s time period, might not show a true network of the immigrants, as immigrants at the base year 2011 might be driven by forces that affect the housing prices and rents. And because of those reasons, similar to (Muller, (2018), I abandon the IV estimator and focus on results from the normal fixed-effects model.

Table 2: Fixed-effects Results

	Log of Flat				Log of House			
	Rent		Price		Rent		Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrants/pop t-1	0.594*	0.653**	1.193***	1.368***	0.973***	1.031***	0.841***	0.904***
	(0.327)	(0.329)	(0.448)	(0.456)	(0.292)	(0.303)	(0.290)	(0.296)
Disposable income € (t-1)	0.000*		0.000		0.000		0.000***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Unemployment rate (t-1)	0.010***		0.031***		-0.006		0.009**	
	(0.003)		(0.007)		(0.005)		(0.004)	
Disposable income € (t-2)		0.000		0.000		0.000		0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
Unemployment rate (t-2)		0.008***		0.025***		-0.011**		0.007
		(0.003)		(0.007)		(0.005)		(0.005)
Number of observations	2709	2709	2709	2709	2709	2709	2709	2709
R^2	0.046	0.039	0.045	0.034	0.010	0.013	0.047	0.046
Number of districts	387	387	387	387	387	387	387	387

Note: Robust standard errors clustered by government district in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: IV Results

	Log of Flat				Log of House			
	Rent		Price		Rent		Price	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Immigrants/pop t-1	-0.490***	-0.494***	-0.150	-0.159	0.085	0.185	0.068	0.063
	(0.177)	(0.180)	(0.329)	(0.332)	(0.220)	(0.234)	(0.264)	(0.265)
Disposable income € (t-1)	0.000***		0.000**		0.000		0.000***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Unemployment rate (t-1)	0.014***		0.036***		-0.003		0.012***	
	(0.003)		(0.008)		(0.005)		(0.004)	
Disposable income € (t-2)		0.000***		0.000*		0.000		0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
Unemployment rate (t-2)		0.012***		0.030***		-0.008		0.010**
		(0.003)		(0.008)		(0.005)		(0.005)
Number of observations	2709	2709	2709	2709	2709	2709	2709	2709
R^2	0.046	0.036	0.037	0.024	0.001	0.003	0.038	0.035
Number of districts	387	387	387	387	387	387	387	387

Note: Robust standard errors clustered by government district in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

6 Robustness Checks

In order to further support my findings from the FE model, I make use of four types of robustness checks. I first estimate a model by adding a district-year fixed-effects, similar to (Muller, 2018), which can be found in Table 4. I achieve this by adding an interaction term between the year and the district code variables, this allows for separate time trends for each district. Although the results are mostly insignificant, however, we can still observe a positive correlation following the results in Table 2, with coefficients ranging between 0.054% to 0.751%, which a lower than before.

In the second robustness check, I stop using district fixed-effects and replace it with larger geographical areas, transforming it into a state fixed-effects by aggregating the districts into the 16 states of Germany, this leaves me with only 112 observations, which can be found in Table 5. In terms of explanatory power, all but flat rents have similar coefficients, with flat rents having coefficients reaching 1.92. (Borjas, 2006) and (Muller, 2018) discuss how comparisons between those two regions may not show the best results, as effects in districts are no longer considered in the analysis. It is safe to say that the results from Table 5 are by no means the most reliable in terms of the size of the effect, however, they can help support the direction of the effect, which is positive.

Table 4: Robustness Check I

	Log of Flat				**Log of House**			
	Rent		**Price**		**Rent**		**Price**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Immigrants/pop t-1	0.400***	0.416***	0.751	0.682	0.253	0.215	0.090	0.052
	(0.150)	(0.151)	(0.484)	(0.486)	(0.415)	(0.416)	(0.265)	(0.266)
Disposable income € (t-1)	0.000		-0.000		-0.000		-0.000	
	(0.000)		(0.000)		(0.000)		(0.000)	
Unemployment rate (t-1)	-0.006**		-0.021***		-0.008		-0.004	
	(0.002)		(0.008)		(0.007)		(0.004)	
Disposable income € (t-2)		-0.000		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Unemployment rate (t-2)		-0.004*		-0.023***		-0.021***		-0.008**
		(0.002)		(0.007)		(0.006)		(0.004)
Number of observations	2709	2709	2709	2709	2709	2709	2709	2709
R^2	0.669	0.668	0.508	0.509	0.357	0.361	0.636	0.637
District-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Number of districts	387	387	387	387	387	387	387	387

Note: Standard errors clustered by government district in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Table 5: Robustness Check II

	Log of Flat				Log of House			
	Rent		Price		Rent		Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrants/pop t-1	1.836***	1.915***	0.856*	0.921*	0.942**	0.937**	0.774	0.753
	(0.291)	(0.287)	(0.507)	(0.511)	(0.367)	(0.358)	(0.521)	(0.515)
Disposable income € (t-1)	-0.000**		0.000		-0.000**		0.000***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Unemployment rate (t-1)	-0.004		0.016**		-0.021***		-0.020***	
	(0.004)		(0.007)		(0.005)		(0.007)	
Disposable income € (t-2)		-0.000		-0.000		-0.000		0.000
		(0.000)		(0.00000)		(0.000)		(0.000)
Unemployment rate (t-2)		-0.006		0.015*		-0.025***		-0.022***
		(0.004)		(0.008)		(0.006)		(0.008)
Number of observations	112	112	112	112	112	112	112	112
R^2	0.330	0.348	0.149	0.134	0.170	0.207	0.328	0.343
Number of districts	387	387	387	387	387	387	387	387

Note: Standard errors clustered by government district in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Moving now to the third robustness check, which can be found in the appendix in Table 9. I take a different approach, where I estimate slightly different dependant variables, where originally the variables were of full prices and rents in here I estimate the prices and rents per m^2, this allows to get the prices that are not affected by the quality of the dwellings, it's important to note that the quality of dwellings do change from one district to another, and this is takin into account by using fixed-effects. However, the quality here refers to features in the house, so for example, a feature of having a cinema room in a house, which drives the price of the house greatly, is now removed as only the type, size and location of the dwelling is considered. With that said the results are significant and similar to the ones in the original model, with coefficients ranging between 0.589% to 1.86%. Between these results and the results from Table 2 we can draw a picture of immigrant preference towards dwellings, this will be discussed later.

The fourth and final robustness check, which can be found in Table 10 in the Appendix, replaces the main explanatory variable, the number of immigrants, with the population level in district (i) at time (t). The motivation behind the sensitivity test is assessing the native populations' migration patterns given the inflow of immigrants, which was discussed by (Sá, 2015) and (Saiz, 2007). it shows generally negative coefficients apart from flat prices, they range from -0.778% to -0.188%, this might suggest that immigrants could be pushing out natives from the districts. It is difficult to say for certain, but more studies on native population distribution have to be done in order to conclude this matter.

From looking at the results of the robustness check we can conclude that they do support the results of the model in Table 2 in terms of the sign of the coefficients, however, the size of the coefficients is up for debate. Other robustness checks could have been used if data were available. For example, looking at wage distributions or the quality of housing could have provided more depth to the research.

7 Discussion

From the results we found that a rise of the immigrant population relative to the overall population by 1% increase dwelling prices and rents by 0.59% to 1.19%, however, this is not a solid conclusion, given that the results are separated into four different types of dwellings, we need to asses them separately. OECD/European Union (2015) discussed how immigrants tend to own fewer dwellings in Europe, however, when it comes to Germany the rate of ownership between natives and immigrants(adjusted to age and income) is pretty much the same, with 41% immigrants and 45% natives owning their dwellings. This notion is not quite supported by the results, we can see that results from house prices and rents do support it, given that coefficients of house rents are generally higher than house prices (see Table 2 and Table 9), this could be because immigrants rent more than buy. However flat rents and prices do not support this notion, rather oppose it as effects on flat prices is generally larger than flat rents. It is difficult to pinpoint the cause of this difference between the two types of dwellings, and more research into the housing market has to be conducted.

This uncertainty in the size of the effect can be blamed at the biased nature of the model which can be caused by aspects, first of which is the use of the normal fixed effects model, not the IV model. As the IV solves the problem of the non-randomness of immigrant allocation, however the IV, as mentioned before, suffers from several problems including not a far enough in time base year, and insignificant results. Second of all the model specification is not optimal, there are many more control variables that could have affected the price which has not been included. A few variables would be, the number of dwellings, which would have captured the supply side of the housing market, given that the population levels capture the demand side. Another variable that has been heavily used in previous literature is the crime rate, which can push prices down as it increases. But as a result of limited data availability, I was unable to include these variables, if they were available a more solid result could have been achieved.

However, it is still important to notice the importance of the results of this paper, by assessing the effect on different types of dwelling, we are able to get results that can help policymakers with achieving equilibrium within the housing market. By finding out what sub-market (e.g. flat prices) is affected most by influxes in immigration, policymakers can then target those markets and increase the construction of dwellings, this could balance the market and help avoid increased prices. Also, this could help tackle the issue of over-crowding within immigrant household as mentioned by (OECD/European Union, 2015).

8 Conclusion

As mentioned before the body of literature that surrounds immigrants and its effects on the housing market has been growing ever since the start of the 21st century. With the large influx of immigrants into the EU starting from 2015, it was no surprise that Germany was the highest country to receive immigrants, given its large economy.

Using data on house/flat prices/rents in 387 German government districts between the years 2012 and 2018, I was able to find that immigrants have an overall positive effect on the housing market within Germany. A 1% increase in the number of immigrants relative to the population raises flat rents between 0.595% to 0.653%, while flat prices increase between 1.19% to 1.37%. When looking at house rents the effect ranged between 0.973% and 1.03%, while house prices ranged between 0.841% and 0.904%. We can then say that the overall effect of an increase of 1% in immigrants relative to the population ranges between 0.95% and 1.37%.

As mentioned before the fixed-effects model suffers from bias, and although we can't measure the size of the bias, we still have a somewhat solid conclusion on the effect of immigration on the German housing market. Those results may not effectively help policymakers, but what they can do is give an initial view of the market, which can then be taken and researched more thoroughly to achieve a more consolidated result.

(5588 words)

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10 Appendix

Table 6: Share-Shift Ratios Descriptive Statistics

Cluster	(1) Mean	(2) St. Dev.	(3) Min	(4) Max
A	0.002534	0.011244	0	0.128732
B	0.002533	0.008857	8.06E-05	0.160506
C	0.002529	0.005842	6.74E-05	0.08098
D	0.002539	0.005021	4.99E-05	0.056221
E	0.002533	0.005921	0.000103	0.070745
F	0.002538	0.004979	4.53E-05	0.063924
G	0.002527	0.009573	0	0.150154
H	0.002522	0.008168	0	0.119656
I	0.002533	0.007335	0.000115	0.105598
J	0.002525	0.013649	0	0.226263
K	0.002535	0.006047	4.44E-05	0.054393
L	0.002531	0.006857	1.52E-05	0.085635
M	0.002533	0.008626	8.65E-06	0.146705
N	0.002533	0.007781	2.65E-05	0.113912
O	0.002536	0.005486	0	0.050424
P	0.00254	0.006389	0	0.08399
Q	0.002539	0.006798	0	0.072337
R	0.002537	0.008011	1.22E-05	0.10042

Table 7: IV Data Descriptive Statistics

Variables	N	(1) Mean	(2) St. Dev.	(3) Min	(4) Max
Flat Rent €	2,709	491.8	134.0	260.7	1,274.0
Flat price €	2,709	161,780.7	77,971.4	36,756.2	706,461.2
House rent €	2,709	972.5	317.1	419.6	2,694.8
House price €	2,709	303,380.0	180,233.1	68,327.8	1,634,153.0
Immigrants	2,709	22,694.6	49,497.0	476.5	803,119.0
Population t-1	2,709	206,304.7	241,366.4	34,011	3,613,495
Disposable income € t-1	2,709	4,321,210.0	5,017,573.0	624,347	73,067,596
Unemployment rate t-1	2,709	6.0	2.9	1.2	16.7
Disposable income € t-2	2,709	4,209,320.0	4,872,346.0	621,551	69,310,763
Unemployment t-2	2,709	6.3	3.0	1	17

Table 8: Immigration estimation Descriptive Statistics

Variables	N	(1) Mean	(2) St. Dev.	(3) Min	(4) Max
Number of immigrants	360	412,987.1	887,319.5	3,603	3,726,985
Infant mortality per 1000 people	360	26.7	20.2	2.9	99.7
GDP per capita in euro	360	9,914.8	13,074.0	254.7	49,152.1
Population	360	376,659,285.0	434,737,581.0	18,936,811	1,792,203,048
Battle deaths	360	2,673.4	8,226.5	0	69,781

Table 9: Robustness Check III

	Log of Flat				**Log of House**			
	Rent per m²		**Price per m²**		**Rent per m²**		**Price per m²**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Immigrants/pop t-1	0.589**	0.665***	0.889***	1.040***	0.723***	0.791***	1.120***	1.186***
	(0.239)	(0.240)	(0.333)	(0.339)	(0.215)	(0.226)	(0.258)	(0.262)
Disposable income € (t-1)	0.000***		0.000***		0.000*		0.000***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Unemployment rate (t-1)	0.018***		0.028***		0.001		0.012***	
	(0.002)		(0.008)		(0.004)		(0.004)	
Disposable income € (t-2)		0.000***		0.000***		0.000*		0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
Unemployment rate (t-2)		0.016***		0.024***		-0.003		0.010**
		(0.002)		(0.007)		(0.003)		(0.004)
Number of observations	2709	2709	2709	2709	2709	2709	2709	2709
R^2	0.168	0.146	0.059	0.048	0.017	0.018	0.082	0.081
Number of districts	387	387	387	387	387	387	387	387

Note: Robust standard errors clustered by government district in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Table 10: Robustness Check IV

	Log of Flat				Log of House			
	Rent		Price		Rent		Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Population/pop t-1	-0.198	-0.188	0.872^{*}	0.910^{*}	-0.550	-0.576	-0.778^{***}	-0.740^{**}
	(0.176)	(0.178)	(0.465)	(0.469)	(0.355)	(0.356)	(0.296)	(0.297)
Disposable income € (t-1)	0.000^{***}		0.000^{**}		0.000		0.00000^{***}	
	(0.000)		(0.000)		(0.000)		(0.000)	
Unemployment rate (t-1)	0.012^{***}		0.035^{***}		-0.003		0.012^{***}	
	(0.001)		(0.004)		(0.003)		(0.002)	
Disposable income € (t-2)		0.000^{***}		0.000^{**}		0.000		0.00000^{***}
		(0.000)		(0.000)		(0.000)		(0.000)
Unemployment rate (t-2)		0.010^{***}		0.029^{***}		-0.007^{**}		0.010^{***}
		(0.002)		(0.004)		(0.003)		(0.003)
Number of observations	2709	2709	2709	2709	2709	2709	2709	2709
R^2	0.033	0.023	0.039	0.025	0.002	0.004	0.040	0.037
Number of districts	387	387	387	387	387	387	387	387

Note: Standard errors clustered by government district in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Table 11: Variable Description and Sources

Variable	Description	Source
Infant mortality	The number of infants dying before reaching one year of age, per 1,000 live births in a given year	The World Bank Open Database
GDP per capita in USD	is the gross domestic product divided by the mid-year population in a given country at a given time	The World Bank Open Database
Total population world	total population of a country at a given time	The World Bank Open Database
Battle deaths	Deaths that are a result of war within a country at a given time	The World Bank Open Database
Prices	Includes averages of flat prices, flat rents, house prices and house rents also includes a version of the prices per meter squared	Empirica Systeme
Immigrants	Measures all non-Germans living in Germany in a given area at a given time	Genesis-online (German Federal Statistical Database)
Population	Measures the population level in a given area at a given time	Genesis-online (German Federal Statistical Database)
Unemployment	Measures the unemployment level on all income levels in a given area at a given time	Genesis-online (German Federal Statistical Database)
Disposable Income	Measures the total disposable income of people living in a given area at a given time	Genesis-online (German Federal Statistical Database)