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Rental Prices in Germany: A Comparison Between Migrants and Natives

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Abstract

This paper deals with the question of whether migrants in Germany pay a rent premium for apartments of comparable quality and neighborhood characteristics. We use a twostep selection-correction model augmented by a control function to account for nonrandom neighborhood choice. The estimation sample is a uniquely assembled panel comprising the German Socio-Economic Panel (SOEP), information on household and apartment characteristics, as well as georeferenced data describing neighborhood quality. We find no evidence that having a migrant background is directly associated with higher rent. Migrants may nevertheless face higher rents by settling in neighborhoods populated by a high share of foreigners, which we find has a positive and statistically significant relationship with the rent.

JEL Classification: R23, J15, R21

Keywords: Migrants; discrimination; housing market

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1 Lea Eilers, RWI and RUB; Alfredo R. Paloyo, RWI and Centre for Human and Social Capital Research, University of Wollongong; Colin Vance, RWI, RGS Econ, and Jacobs University Bremen. *– We gratefully acknowledge the support of the Leibniz Gemeinschaft via the project "Neighborhood Effects: The Analysis of Individual Behavior in a Social Context" financed as part of the Pakt für Forschung und Innovation. Personal acknowledgments are suppressed for purposes of review.* *– All correspondence to: Lea Eilers, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: lea.eilers@rwi-essen.de*

1 Introduction

This paper is concerned with the discrimination of migrants within the context of the rental housing market in Germany. In particular, we examine whether people with a migration background pay a comparatively higher rent in Germany than those without a migration background. Credibly estimating this rental differential is nontrivial when we allow for selection into renting and when we acknowledge that indivdiuals choose their neighborhoods based on observable and unobservable housing features and neighborhood amenities. Our principal contribution is to estimate this rental premium while controling for endogeneity arising out of selection into renting as well as housing segregation (i.e., nonrandom sorting into neighborhoods). To accomplish this, we construct a unique dataset by combining information across many different data sources that allows us to simultaneously characterize the tenant, the rental unit, and the neighborhood.

The rental housing market in Germany is of interest for a number of reasons. First, a large share of German residents live in a rented or a sublet dwelling. While the European Union average for homeownership is about 70 percent, the corresponding share in Germany is only about 53 percent—the lowest among 27 of the 28 EU countries.[1] Second, once a rental contract has commenced, it is very difficult to evict a tenant because of the strong protections for tenants that exist in the German legal system. In many circumstances, a landlord cannot evict a tenant even when the latter has refused to pay rent. Third, there is excess demand in the rental housing market, especially in larger cities [Fitzenberger and Fuchs 2017; Auspurg, Hinz and Schmid 2017]. In this sense, landlords and real estate agents have a strong gatekeeper role to play in deciding who can rent an apartment [Auspurg, Hinz and Schmid 2017]. In conjunction with the fact that tenants are almost never evicted, landlords are especially careful in commencing a tenancy relationship. Landlords can indeed exercise significant market power in these bilteral negotiations, including, of course, the potential to unjustifiably discriminate against "undesirable" tenants based on ethnic origin or migration background.

Current evidence indicates that people with a migration background in Germany pay a rental premium [Winke 2016].[2] It has been suggested that this rental premium may be due to prejudicial price discrimination exhibited by landlords over migrant renters [Kilic 2008]. Indeed,

[1] See https://goo.gl/5Xq0PP. No information is provided for Estonia.

[2] In a correspondence study published recently, Auspurg, Hinz and Schmid [2017] demonstrate that Turkish applicants for a rental properties in Munich are less likely to receive a response from a landlord.

most migrants self-report being discriminated against when seeking housing.[3] This action goes against most laws requiring equal treatment of different ethnic groups.[4] Thus, determining whether there truly is a payment differential between migrants—including people with a migration background—and comparable natives becomes an important question, particularly in light of the nearly 1 million refugees that entered Germany in 2015.

In addressing this question, it is important to recognize that the observed empirical pattern in the rental market may be caused by a number of factors that have little to do with prejudice. For instance, migrants may self-select into neighborhoods because of network effects [Borjas 2000], or migrants may be in certain properties because of other characteristics that correlate with having a migration background, such as a higher likelihood of being a smoker.[5] As such, any ostensible discrimination in rental payments may be generated by benign determinants that should not necessarily invite a policy response to correct a purported social injustice.

We extend the previous literature by making the following contributions. First, we estimate the difference in rental payments between migrants and natives while simultaneously accounting for endogenous neighborhood choice and selection bias arising out of the characteristics of renters. In particular, we use a two-step Heckman selection model [Heckman 1979] that is augmented with a control function approach [Bayer and Ross 2006] to account for selection on the basis of unobserved neighborhood characteristics. The first step of our selection model is to estimate the likelihood of being a tenant, since about 43 percent of our sample are either tenants or sublessees. Second, we estimate the main outcome equation using a uniquely assembled panel dataset that draws from several sources: the German Socio-economic Panel (SOEP), the DIW-IAB-RWI-Neighborhood Panel, the RWI-GEO-GRID, the Federal Statistical Office of Germany (Destatis), and the RWI-GEO-RED.[6] Thus, we are also able to control for a vast suite of covariates that were unaccounted for in the previous literature, thereby further reducing potential omitted-variable bias.

Our estimates indicate that migrants are not charged higher rental payments relative to their native counterparts. This is true both when we control for selection into renting and when

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[3] See "Foreigners not welcome: racism in Germany's housing market" in `https://goo.gl/9CLZMt`.

[4] Particularly in Germany, the General Act on Equal Treatment proscribes discrimination on the basis of, *inter alia*, ethnic origin. [AGG 2006]

[5] In our sample, 46 percent of nonnatives are smokers compared to only 44 percent of the natives, with the difference being statistically significant. See Table B.2 in the Appendix.

[6] These datasets are explained in more detail in Section 3.

we introduce nonrandom neighborhood sorting. Taken together, our estimates do not support the idea that migrants are discriminated by being charged a higher rent.

Our analysis does not, however, allow us to address the possibility of access discrimination, that is, whether migrants are disproportionately declined rental properties, which could indirectly bear on the rent paid by limiting where they can seek apartments. In this regard, we find a positive and statistically significant association between the rent paid and the share of foreigners in the neighborhood. To the extent that migrants settle in neighborhoods populated by a high share of foreigners, they may consequently have to pay a higher rent than were they to settle elsewhere. Indeed, we cannot rule out the existence of a discriminatory sorting process that compels migrants to search for apartments among a circumscribed set of neighborhoods where landlords charge a rental premium.

The remainder of this paper is structured as follows. Section 2 present a description of the methodology. Section 3 describes the data construction and provides descriptive statistics. Estimation results are presented in Section 4. We conclude in Section 5.

2 Empirical Strategy

Considering that almost half of our sample are homeowners (i.e., zero rental payments), we conceptualize the rent paid as a two-stage decision-making process where the agent is first deciding whether to rent and, conditional on having rented, deciding how much rent is paid. It is necessary to account for the selection into renting if the observed and unobserved characteristics of renters that make them different from non-renters, including their migration background, also influence the rental price.

To empirically implement this, we use the two-step Heckman [1979] selection model in which the first stage is used to estimate the probability of being a renter:

$$\Pr\left[y_{ijt}=1|\mathbf{z}\right]=\Phi\left(\mathbf{z}'_{ijt}\boldsymbol{\beta}\right), \tag{1}$$

where y_{ijt} is an indicator variable for renting an apartment for person i in neighborhood j at time t, while the vector $\mathbf{z}_{ijt}$ includes variables that we use to predict the decision to rent, such as smoking status, age, educational attainment, and others.[7] The parameter vector $\boldsymbol{\beta}$ is to be estimated. For the probit case, we take the index function $\Phi(\cdot)$ to be the cumulative distribution function of the standard Normal distribution. As conventional in the literature, we call Equation (1) the selection or participation equation.

After estimating $\boldsymbol{\beta}$ from Equation (1) via probit, we obtain the nonselection hazard,

$$\lambda\left(\mathbf{z}'_{ijt}\widehat{\boldsymbol{\beta}}\right) = \frac{\phi\left(\mathbf{z}'_{ijt}\widehat{\boldsymbol{\beta}}\right)}{\Phi\left(\mathbf{z}'_{ijt}\widehat{\boldsymbol{\beta}}\right)},$$

where $\widehat{\boldsymbol{\beta}}$ is the estimated parameter vector and $\phi(\cdot)$ is the standard Normal density function. We henceforth refer to $\lambda_{ijt} \equiv \lambda\left(\mathbf{z}'_{ijt}\widehat{\boldsymbol{\beta}}\right)$ as the inverse Mills ratio.

In the second stage (i.e., the outcome equation), we specify the rent paid, w_{ijt}, as a function of vectors of explanatory variables augmented by the inverse Mills ratio, λ_{ijt}:

$$w_{ijt} = \mathbf{x}'_{ijt}\boldsymbol{\xi} + \mathbf{a}'_{ijt}\boldsymbol{\delta} + \mathbf{n}'_{jt}\boldsymbol{\gamma} + \mu\lambda_{ijt} + \epsilon_{ijt},$$

where the vector $\mathbf{x}_{ijt}$ is a constant plus a collection of individual and household characteristics, such as income, employment status, civil status, age, and the number of children living in the household; $\mathbf{a}_{ijt}$ is a vector of apartment characteristics, such as size, condition, and amenities (e.g., having a garden or balcony); $\mathbf{n}_{jt}$ is a vector of observable neighborhood characteristics, such as the share of migrants, share of families and couples, and the unemployment rate; and ϵ_{ijt} is the idiosyncratic error term. The parameters and vectors of parameters $\boldsymbol{\xi}$, $\boldsymbol{\delta}$, $\boldsymbol{\gamma}$, and μ are estimated via ordinary least squares. The inverse Mills ratio is included to account for the selection bias that arises from differences in the characteristics of renters and non-renters.

Although the Heckman [1979] model is theoretically identified, we follow convention in securing identification by additionally employing an exclusion restriction, namely by adding a variable in the participation equation that is absent from the outcome equation. In our case, we specify that being a smoker and having a partner who is a smoker are likely going to affect the probability of being a tenant, but it has no impact on the rent charged by the landlord.

While the selection model outlined above can account for differences in the renters and non-renters, we have yet to address the bias arising out of nonrandom neighborhood sorting. We

[7] Tables with the complete list of covariates are presented in the Appendix.

can allow for this unobserved neighborhood effect by augmenting the estimation equation with the variable ν_{jt}, which represents unobservable factors that drive endogenous location choice [Bayer and Ross 2006]:

$$w_{ijt} = \mathbf{x}'_{ijt}\boldsymbol{\xi} + \mathbf{a}'_{ijt}\boldsymbol{\delta} + \mathbf{n}'_{jt}\gamma + \mu\lambda_{ijt} + \kappa\nu_{jt} + \varepsilon_{ijt}. \tag{2}$$

Although ν_{jt} is ultimately unobserved, Epple and Platt [1998] have shown that as neighborhood quality increases, we can expect that average house prices will increase in concert. We can thus use a function of house prices as a proxy for neighborhood characteristics. Specifically, we can estimate a hedonic house price model as follows:

$$\log(p_{mjt}) = \mathbf{h}'_{mjt}\boldsymbol{\eta} + \mathbf{n}'_{jt}\boldsymbol{\zeta} + \boldsymbol{\tau}_t + \nu_{mjt}, \tag{3}$$

where p_{mjt} is the price of house m in neighborhood j at time t. The vector $\mathbf{h}_{mjt}$ contains the constituent characteristics of the housing unit, the vector $\mathbf{n}_{jt}$ is a collection of observable neighborhood characteristics, and $\boldsymbol{\tau}_t$ represents a vector of period fixed effects, with $\boldsymbol{\eta}$ and $\boldsymbol{\zeta}$ representing vectors of parameters to be estimated.

The error term, ν_{mjt}, represents unobserved, time-varying factors that influence average house prices. After estimation of Equation (3) via OLS, we calculate the residuals, and then take the average per year–neighborhood combination:

$$\overline{\nu}_{jt} = \left(\frac{1}{M}\right)\sum_{m=1}^{M}\widehat{\nu}_{mjt},$$

where $\widehat{\nu}_{mjt}$ are the post-estimation residuals from Equation (3). We use $\overline{\nu}_{jt}$ as a proxy for ν_{jt} in Equation (2), resulting in our final outcome equation:

$$w_{ijt} = \mathbf{x}'_{ijt}\boldsymbol{\xi} + \mathbf{a}'_{ijt}\boldsymbol{\delta} + \mathbf{n}'_{jt}\gamma + \mu\lambda_{ijt} + \kappa\overline{\nu}_{jt} + \varepsilon_{ijt}. \tag{4}$$

Note that the unobservable factors that drive neighborhood choice are allowed to vary over time. Equation (4) is estimated using pooled OLS, and we report robust standard errors.

Since our constructed dataset includes an extensive list of potential determinants of rental payments, we can progressively include covariates that capture various aspects of the individual, the rental unit, and the neighborhood. This allows us to examine how the estimated migrant premium (or penalty) from our baseline specification changes as we include additional control variables, particularly when we control for selection based on being a tenant or homeowner and on endogenous neighborhood choice.

3 Data Description

The empirical analysis is based on a unique dataset that combines longitudinal household data from the German Socio-Economic Panel (SOEP) and postcode-level geographic data from the RWI-GEO-GRID [RWI 2016a,b,c; Budde and Eilers 2014].[8] We are able to merge the latter geocoded data to the SOEP using the DIW-IAB-RWI Neighborhood Panel [DIW and RWI 2016; Bügelmeyer et al. 2015] on the basis of postcode areas. We also use house prices and house characteristics from the RWI-GEO-RED [an de Meulen, Micheli and Schaffner 2014], a dataset that contains information from the largest real-estate platform in Germany, *ImmobilienScout24*.

The SOEP, which started in 1984 and is managed by the German Institute of Economic Research (DIW), is a representative household panel study in which annual personal interviews are conducted with all adult household members to obtain information on a host of socioeconomic, demographic, and health characteristics of household members, including some information on the characteristics of the dwelling [Schupp et al. 2015]. About 11,000 households consisting of around 20,000 persons are surveyed annually. These individuals provide information useful for this study, such as household composition, family background, information on being a tenant or homeowner, apartment quality, and rental payments. The information on being a tenant or owner (y_{ijt}) and the real net basic rent (w_{ijt}) are used as dependent variables in the participation and outcome equations, respectively, of the two-step Heckman [1979] selection model.[9]

We have individual-level data on the household head, his or her partner, and information that pertains to the whole household. Information about the household head and the partner includes age, sex, civil status, and an indicator for having a migration background. We also

[8] The data used in this paper was extracted using the Add-On package PanelWhiz for Stata®. PanelWhiz <http://www.PanelWhiz.eu> was written by Dr. John P. Haisken-DeNew <john@PanelWhiz.eu>. See Hahn and Haisken-DeNew [2013] and Haisken-DeNew and Hahn [2010] for details. The PanelWhiz generated .DO file to retrieve the data used here is available from the authors upon request. Any data or computational errors in this paper are our own.

[9] The net basic rent is the self-reported net rent deflated using the consumer price index provided by DESTATIS [2015].

control for employment (full-time, part-time, and no employment) and educational attainment (ISCED classification). We create income tertiles (low, medium, high income) to account for differing economic status. Moreover, we consider the household composition by including the number of adults living in the household and the number of children.

Our primary variable of interest is the migration background, which is captured in the SOEP by a binary variable indicating whether an individual is a first- or second-generation migrant. Based on this variable, we create three indicators for couples where both members are migrants, both members are natives, and one member is a migrant and the other a native. Singles are grouped with either the native or migrant couples. In our sample, about 18 percent are first- or second-generation migrants and about 10 percent have a partner who is either a first- or second-generation migrant.

For our exclusion restriction, we use information on whether the household head is a smoker and whether the partner of the household head is a smoker. For unpartnered individuals, the variable indicating the smoker status of the partner is set equal to 0. Whether the individual is a smoker is only asked every two years in the SOEP. To fill in the missing information, we set the variable equal to the value the year before and the year after if the values of the indicator match. If the information the year before and the year after do not match, then we predict the probability of being a smoker based on observable characteristics using the whole sample, and set the variable to indicate a smoker if the predicted probability is greater than 0.3.[10] We note that a smoking household head rents an apartment more often (66 percent) than a non-smoking household head (43 percent) as shown in Table B.1.

Neighborhood information is obtained from the RWI-GEO-GRID data. This includes the share of foreigners in a postcode area and the unemployment rate. To capture the supply side of the market, we also include the annual vacancy rate, a state-level variable that is obtained from the Federal Statistical Office. For the empirical analysis, the neighborhood characteristics are merged with the household SOEP data at the level of about 3,680 postcode areas. Furthermore,

[10] To empirically interpolate smoker status for the years with missing observations, a probit model of the following form is seperately estimated for the household head and the partner:

$$\Pr\left[s_{ijt} = 1|\mathbf{k}\right] = \Phi\left(\mathbf{k}'_{ijt}\boldsymbol{\theta}\right),$$

where s_{ijt} is an indicator variable for smoking for person i in neighborhood j at time t, while the vector $\mathbf{k}_{ijt}$ includes socioeconomic variables that we use to predict the decision to smoke. The parameter vector $\boldsymbol{\theta}$ is to be estimated. Control variables are the same as in Equation (1), but we additionally control for the health status of the individual using self-assessed health in the equation to predict smoking status.

the information on the vacancy rate is merged at the level of the 16 federal states in Germany (ten states from former West Germany plus Berlin and five federal stated from the former East Germany). Households living in price-reduced (i.e., socialized or social) dwellings are dropped.[11]

Referring to Tables B.2, people with a migration background tend to live in areas where there is a higher share of foreigners (0.9 vs. 0.7). This may indicate that migrants self-select into neighborhoods where they can potentially enjoy the benefits of having a local immigrant network of people coming from their own countries of origin, although we do not directly observe their countries of origin in the variable used to capture the share of foreigners in a postcode area. We can also visually verify this by examining Figure 1, which is a map of Germany where darker areas represent higher foreigner shares. The first thing to note is that there are very few foreigners living in former East Germany save for Berlin. Second, cities tend to have higher immigrant shares: Berlin, Hamburg, Munich, Stuttgart, Frankfurt, and the Ruhr Area (comprising a number of major cities) stand out. Again, this suggests that migrants self-select into these neighborhoods, and the factors that determine their location choice may not always be observable to the econometrician.

Our analysis focuses on the period 2007–2015 since the real-estate data are available from 2007 onwards. The resulting sample is an unbalanced panel with 48,133 observations consisting of 14,494 households. One disadvantage of this dataset is that we are as yet unable to account for the aforementioned recent influx of migrants in Germany. That said, this is the first dataset that allows us to control for neighborhood characteristics at the level of detail that the real estate data is able to provide.

4 Results

4.1 Preliminary Evidence

As a preview, we mention at the outset that none of the models estimated present evidence that having a migrant background or being a native who has a partner with a migrant background is associated with a higher rent. Indeed, even a simple descriptive comparison—one

[11]Households stated in the SOEP as tenants but paying no rent are excluded. Moreover, households paying a reduced rent or living in government subsidized apartments *(Sozialwohnungen mit Wohnberechtigungsschein nach § 5)* are excluded since these rents are independent from the local refenrence rent. These observations comprise about 11 percent of the original sample.

that cross-tabulates by urban and non-urban location—suggests only small differences in rent, with migrants paying slightly more per square meter than natives in urban areas and the same amount in rural areas (Table 1).

Table 1
Real Net Basic Rent per Square Meter in Euro

	Migrants	Natives	Difference	Std. Err.
Full sample	6.19	6.05	0.14	0.03^{*}
Rural subsample	5.40	5.40	0.01	0.04
Urban subsample	6.44	6.38	0.58	0.03

Notes.—The t-test is based on 22,637 observations in total, with 17,439 natives and 5,198 migrants in the full sample. The number of observation for migrants is 1,219 in rural and 3,979 in urban areas. The number of observation of natives is 5,784 in rural and 11,655 in urban areas. * $p < 0.01$.
Source.—Authors' calculations based on SOEP.

To test whether this conclusion holds up to the inclusion of control variables, our main results are based on the estimation of Equation (4) in Section 2, where we model the rental price as a function of observable characteristics and including a proxy for unobserved neighborhood characteristics.

4.2 Do Migrants Pay Higher Rent?

Before turning to the full model, we briefly discuss the results of our auxiliary regressions, specifically the probit estimation results of our selection equation and an OLS regression of the outcome equation with and without the inverse Mills ratio. These are presented in Table 2, where we only report the coefficients of particular interest. The first column shows the results of the probit estimates of Equation (1), where we examine the determinants of being a tenant. The second column is an OLS regression of rent paid against a set of control variables. In Model (3), we again regress rent as a function of control variables, but now including the inverse Mills ratio derived from the selection equation.

Looking at Model (1), couples in which both partners are migrants (including single migrants) are more likely to be a tenant than a homeowner. Based on the calculation of the marginal effects (not reported), the probability that a migrant couple rents is about 11 percentage points higher than a native couple. Being in a mixed couple also increases the likelihood of being a tenant, with the marginal effect somewhat smaller at 8 percentage points. Both estimates are statistically significant at the one-percent level.

Table 2
Probability of Being a Tenant (Selection) and Rent Paid (Outcome)

	Selection Equation Model (1)	Outcome Equation Model (2)	Outcome Equation Model (3)
Migrant couple	0.377*	−0.001	0.006
	(0.056)	(0.012)	(0.013)
Mixed couple	0.246*	−0.002	0.002
	(0.036)	(0.007)	(0.008)
Smoker	0.253*		
	(0.026)		
Partner is smoker	0.110*		
	(0.027)		
Inverse Mills ratio			0.033
			(0.024)
Household characteristics	yes	yes	yes
Apartment characteristics	yes	yes	yes
Neighborhood characteristics	no	no	no
Observations	48,133	22,637	22,637
Adjusted R^2		0.285	0.285

Notes.—Indicators for the observation year are included. The constant is not reported. Standard errors are robust to clustering at the household level and are presented in parentheses. * $p < 0.01$.
Source.—Authors' calculations based on SOEP, Destatis and RWI-GEO-GRID.

Concerning the variable we use to secure parameter identification in the Heckman model, the coefficients for being a smoker and for having a partner who smokes are both statistically significant and have the expected positive sign, as can be seen in Model (1). In fact, the estimated coefficient on the household head being a smoker is of about the same magnitude as the corresponding estimates for the migrant indicators, suggesting that smoking status is an an equally important determinant for the probability of being a tenant.

The results for the outcome equations in Models (2) and (3) model rent paid per square meter. The two columns are distinguished by the incluson or exclusion of the inverse Mills ratio derived from the selection equation to account for sample selectivity. The estimates of the indicators for migrant status are uniformly statistically insignificant. The estimate of the coefficient on the inverse Mills ratio, which serves as a test for sample selectivity, is also statistically insignificant. Nevertheless, as its inclusion switches the sign and increases the magnitude of the estimates on the migrant indicators, we continue to include this control in the models that follow.

Building on Model (3) of Table 2, we present further estimation results for the outcome model of rent paid in Table 3, where we again restrict the focus on select variables of interest. Model (4) adds controls for observable neighborhood characteristics while Model (5) additionally controls for unobserved neighborhood quality via our derived proxy variable. The latter corresponds to the fully specified model of Equation (4). The conclusion derived from Table 3, where we use these additional time-varying, neighborhood-level control variables, does not materially depart from our previous statements. Couples in which one or both partners have a migration background do not pay higher rents than natives when simultaneously controlling for nonrandom location choice and selection into being a tenant.

TABLE 3
RENT PAID

	Model (4)	Model (5)
Migrant couple	−0.012	−0.011
	(0.012)	(0.012)
Mixed couple	−0.006	−0.005
	(0.007)	(0.007)
Inverse Mills ratio	0.019	0.015
	(0.023)	(0.023)
Foreigner	1.649*	1.765*
	(0.079)	(0.078)
Proxy for neighborhood quality		0.130*
		(0.009)
Household characteristics	yes	yes
Apartment characteristics	yes	yes
Further neighborhood characteristics	yes	yes
Observations	22,637	22,637
Adjusted R^2	0.325	0.336

NOTES.—Indicators for the observation year are included. The constant is not reported. Standard errors are robust to clustering at the household level and are presented in parentheses. * $p < 0.01$.
SOURCE.—Authors' calculations based on SOEP, Destatis and RWI-GEO-GRID.

While our analysis has uncovered no direct association between migrant status and rent, Columns (1) and (2) of Table 3 present evidence for a possible indirect association via the share of foreigners in the residential area, which has a positive and statistically significant coefficient. This can already be anticipated from Figure 1, illustrating that foreigners tend to live in cities where the rental prices are substantially higher than elsewhere in the country.

A coefficient estimate of 1.77% for the foreigner share is obtained in Model (5) of Table 3, which includes the control for unobserved neighborhood characteristics derived from the residuals of estimating the hedonic model in Equation (3).[12] The coefficient of this control is likewise positive, which is consistent with the model of Epple and Platt [1998], where the constructed proxy variable is construed to capture neighborhood amenities that drive location choice but are

[12]The estimation results from the hedonic pricing model are available in the Appendix.

not reflected in variables that are observable to the econometrician. Higher values of this proxy variable would reflect unobservable features of the neighborhood that drive up rental prices.

At this point, it would be useful to compare our results to those reported in Winke [2016], who finds a statistically significant rental price differential between migrants and natives in Germany, albeit at the 10 percent significance level only. In contrast to the results obtained here, he finds that tenants with a migration background tend to pay about €11 more per month than those without a migration background, or about 2.7 percent higher than the average rent of the latter group. Based on a decomposition analysis, he additionally estimates that about 63 percent of the differential is "unexplained" and may be attributed to unequal treatment.

Our approach is different in a number of ways which may explain the contrasting conclusions. First, we use data for the period 2007 to 2015 whereas Winke [2016] relies on cross-sectional data from 2013. Second, we have much more information on observable and unobservable neighborhood characteristics that drive rental prices and could be correlated with how migrants select into neighborhoods. While some observable neighborhood characteristics are included in his estimates as well, we are able to control for a longer vector of such variables. More importantly, we acknowledge the possibility of endogenous location choice based on unobservable factors, and we explicitly control for this using a proxy for these unobservable factors based on a hedonic pricing model. This is possible because of our uniquely assembled dataset, which offers far more information on important individual, rental unit, and neighborhood features.[13]

Another distinction is that Winke [2016] maintains social housing units in his operational sample while we omit them. Our position is that including the sample of people living in social housing is not helpful in achieving our primary goal of estimating differences in the treatment of migrants and non-migrants in the rental market. Social housing is an entity outside the market where the State is almost fully in control. This is in contrast to the market for non-social housing, which—while regulated—is exactly the market where the majority of the population transact and where instances of prejudicial discrimination can put groups of people at a serious disadvantage.[14]

[13] We also additionally take into account the possiblity that selection into being a tenant could bias the estimation of the rental price differential. However, considering that the inverse Mills ratio is not robustly significant in our models, we do not believe that this issue would present itself as a problem in studies that do not account for it.

[14] Nevertheless, as a robustness check we include social housing and apartments having a reduced rental payment. The results also suggest no evidence of any rental payment penalty for migrants.

Our study is limited by the fact that we are unable to observe the migration background of the property owner or indeed any of his or her characteristics. It is plausible that prejudicial discrimination occurs when there is a mismatch between the background of the landlord and the tenant. That is, we may expect a white, German landlord to give preferential rental rates to a white, German tenant, but to levy a migrant penalty on someone who is non-white; conversely, a Turkish landlord may give preferential treatment to Turkish renters. Information on landlord characteristics, however, is not available in our dataset, and we are consequently unable to test how such a mechanism would influence our results.

Nevertheless, we ran a battery of additional regressions to gauge the robustness of our results. First, we estimated our models for West Germany separately. Second, we estimated our models separately for urban and rural areas. Third, we bootstrapped our regressions to obtain alternative standard errors. Fourth, we used postal code fixed effects to account for time-invariant unobserved characteristics that may affect the outcome. Fifth, we included interactions of the migrant dummies with the share of foreigners to assess whether natives face different rental rates than migrants in neighborhoods with a higher share of foreigners. Finally, we considered neighborhood–year interactions as a way to account for time-varying, unobserved effects which our proxy variable would pick up. None of these specifications indicate that being a first- or second-generation migrant or having a partner who is a first- or second-generation migrant has a statistically significant effect on rent. Moreover, the neighborhood characteristics—share of foreigners and $\overline{\nu}_{jt}$—are significantly related to the rental prices except for the specification which includes postal code fixed effects.[15]

5 Conclusion

Our results do not support the claim that people with a migration background in Germany are charged a higher rent than native Germans. Rent, it would seem, is determined by more traditional factors that are associated with the quality of the dwelling and the socioeconomic standing of the tenant.[16] Although there is previous evidence in the literature that concludes the opposite, our nuanced approach based on more extensive information leads us to conclude

[15] Results for all of these regressions are available upon request.

[16] The coefficient estimates for these variables are available in the Appendix. Factors such as the size of the dwelling, the included amenities (e.g., garden, balcony, central heating), the educational achievement and income of the tenant, and whether the unit is in a good neighborhood are all statistically significant in explaining rent.

that price discrimination based on migration background does not manifest itself in the rental housing market in Germany.

However, this is not to say that there is no discrimination in the rental market. As we have mentioned early on, access discrimination may be a significant problem for migrants. There is evidence—both anecdotal and based on a correspondence study [Auspurg, Hinz and Schmid 2017]—that migrants are immediately declined when they apply for a rental property in certain neighborhoods. This would not only limit their options of where to live, but would also bestow landlords with market power in those remaining neighborhoods where migrants are accepted. Our finding of a positive correlation between the share of foreigners in the neighborhood of residence and the rent paid is consistent with such a process. The key challenge is for the State to ensure that certain groups of people, particularly those with a migration background, are not disadvantaged when they are seeking to rent property. Ensuring equal access is likely to prevent other problems from materializing, such as the ghettoization of certain neighborhoods and the social exclusion of migrants living in these ghettos.

We note as well that we are only able to control for the migration background of the tenant, and that we do not have information on whether the landlord has a migration background, too. As pointed out earlier in the paper, when the ethnic origins of the landlord and the tenant match, we are less likely to expect instances of negative discrimination to occur. However, when the landlord does not have a migration background while the tenant does (and, in addition, is of a different "color"), the likelihood of mistreatment can be reasonably expected to increase. Relatedly, we have thus far only recorded whether people have a migration background, but not exactly their specific origin. This may matter as one news article,[17] citing a member of an advice center for victims of discrimination, indicates "that Muslim women with headscarves and black Africans . . . are most likely to be confronted with discrimination." This is an important avenue to pursue when new datasets with more detailed information allow for this kind of undertaking.

The issues associated with housing migrants is expected to feature even more prominently in the public sphere as refugees or asylum seekers transition into the regular housing market and away from the temporary accommodation provided to them by the State. While we do not observe that migrants are charged a higher rent just because they are migrants, the new residents in Germany comprise a different group from the sort of people with a migration background

[17] See "Foreigners not welcome: racism in Germany's housing market" in `https://goo.gl/9CLZMt`.

that we have thus far observed in our dataset. Future work on this issue would be critical to ensure that these people are afforded equal treatment as guaranteed by the laws of the land.

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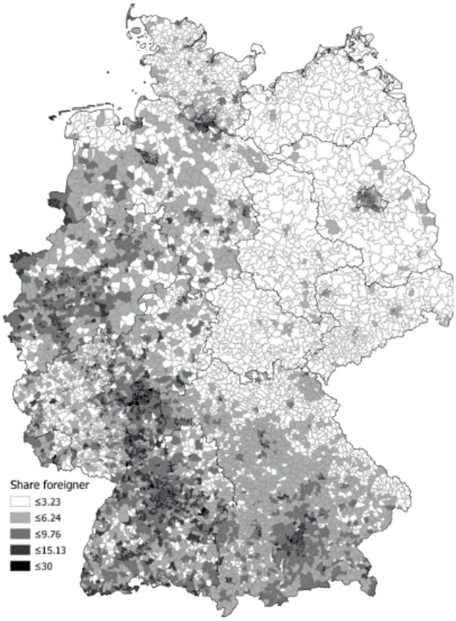
Appendix A Figures

Figure 1
Share of Foreigners, 2012



Note.—The share is presented at the postcode level.
Source.—Authors' calculations based on RWI-GEO-GRID 2012.

Appendix B Summary Statistics

Table B.1
T-test Smoker

	Non-Smoker	Smoker	Difference	Std. Err.
Individual Characteristics				
Partner: Smoker	0.11	0.57	-0.456	0.004***
Either Main tenant or Sub-tenant	0.43	0.66	-0.231	0.005***
Couple: Migrant	0.05	0.04	0.008	0.002***
Couple: Mix	0.15	0.18	-0.026	0.004***
Couple: Native	0.80	0.78	0.018	0.004***
Number of persons	1.98	1.87	0.111	0.011***
No. of children (aged 0-3)	0.02	0.02	0.002	0.001
No. of children (aged 3-6)	0.02	0.03	-0.010	0.002***
No. of children (aged 6-14)	0.06	0.10	-0.037	0.003***
Age	60.25	47.62	12.629	0.149***
Married	0.49	0.32	0.169	0.005***
Sex	0.51	0.55	-0.035	0.005***
Low education	0.12	0.14	-0.022	0.003***
Medium education	0.50	0.65	-0.147	0.005***
High education	0.38	0.21	0.169	0.004***
Full time	0.35	0.54	-0.187	0.005***
Part time	0.12	0.16	-0.045	0.003***
Non-working	0.51	0.19	0.316	0.004***
Unemployed	0.03	0.11	-0.084	0.002***
Partner: Low education	0.06	0.05	0.011	0.002***
Partner: Medium education	0.30	0.20	0.091	0.004***
Partner: High education	0.16	0.06	0.096	0.003***
Partner: Full time	0.16	0.13	0.033	0.003***
Partner: Part time	0.12	0.08	0.038	0.003***
Partner: Unemployed	0.01	0.02	-0.007	0.001***
Partner: Non-working	0.22	0.08	0.134	0.004***
No partner	0.49	0.69	-0.198	0.005***
Household Characteristics				
Low real household income	0.48	0.61	-0.135	0.005***
Medium real household income	0.27	0.24	0.025	0.004***
High real household income	0.25	0.14	0.110	0.004***
Neighborhood Characteristics				
Share empty apartments (state level)	8.18	8.05	0.138	0.035***
Urban regions	0.66	0.64	0.023	0.005***
Foreigner	0.07	0.07	-0.003	0.000***
Unemployment rate	7.53	8.18	-0.657	0.040***

Notes.—T-test is based on 48,133 in total with 31,359 non-smoker and 16,774 observations for smoker. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source.—Authors' calculations based on SOEP.

Table B.2
T-test Tenant: Migration background

	Migrants	Natives	Difference	Std. Err.
Individual Characteristics				
Couple: Migrant	0.19	0.00	0.195	0.003***
Couple: Mix	0.81	0.00	0.805	0.003***
Number of persons	2.05	1.66	0.393	0.016***
No. of children (aged 0-3)	0.03	0.02	0.006	0.003**
No. of children (aged 3-6)	0.03	0.03	0.004	0.003
No. of children (aged 6-14)	0.09	0.08	0.011	0.005**
Age	51.07	51.80	-0.736	0.279***
Married	0.44	0.26	0.176	0.007***
Sex	0.50	0.44	0.065	0.008***
Low education	0.21	0.12	0.089	0.005***
Medium education	0.53	0.59	-0.051	0.008***
High education	0.25	0.29	-0.037	0.007***
Full time	0.42	0.42	-0.004	0.008
Part time	0.16	0.14	0.018	0.006***
Non-working	0.32	0.35	-0.027	0.007***
Unemployed	0.10	0.09	0.013	0.004***
Smoker	0.46	0.44	0.016	0.008**
Partner: Smoker	0.33	0.32	0.011	0.007
Real net basic rent (sq.m.)	6.20	6.06	0.141	0.026***
Real net basic rent	447.18	427.61	19.572	2.866***
No partner	0.55	0.72	-0.169	0.007***
Partner: Full time	0.16	0.11	0.048	0.005***
Partner: Part time	0.10	0.05	0.043	0.004***
Partner: Unemployed	0.04	0.02	0.019	0.002***
Partner: Non-working	0.16	0.10	0.059	0.005***
Partner: Low education	0.12	0.03	0.088	0.003***
Partner: Medium education	0.24	0.18	0.061	0.006***
Partner: High education	0.09	0.07	0.019	0.004***
Household Characteristics				
Low real household income	0.62	0.68	-0.055	0.007***
Medium real household income	0.25	0.22	0.030	0.007***
High real household income	0.13	0.10	0.026	0.005***
Apartment Characteristics				
Size (sq.m.)	73.31	71.42	1.888	0.384***
Has cellar	0.93	0.92	0.005	0.004
Has garden	0.31	0.33	-0.019	0.007**
Has central heating	0.95	0.96	-0.010	0.003***
Has balcony	0.71	0.71	0.003	0.007
In good condition	0.63	0.64	-0.012	0.008
Partial renovation	0.33	0.32	0.008	0.007
Year moved into dwelling	2000.87	1999.47	1.397	0.197***
Neighborhood Characteristics				
Share empty apartments (state level)	7.93	8.48	-0.553	0.061***
Urban regions	0.77	0.67	0.097	0.007***
Foreigner	0.09	0.07	0.020	0.001***
Unemployment rate	7.96	9.11	-1.150	0.069***

Notes.—T-test is based on 22,637 in total with 17,439 natives and 5,198 observations for migrants. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source.—Authors' calculations based on SOEP.

Appendix C Regression Tables

Table C.3
Tenant status and rent paid

	Model 1 (1)	Model 2 (2)	Model 3 (3)
Smoker	0.253***		
	(0.0264)		
Partner: Smoker	0.110***		
	(0.0266)		
Number of persons	-0.109***	-0.00430	-0.00588
	(0.0172)	(0.00421)	(0.00439)
Age of Individual	-0.0774***	-0.00414***	-0.00487***
	(0.00534)	(0.000925)	(0.00108)
Age squared (÷ 1000)	0.454***	0.0499***	0.0523***
	(0.0481)	(0.00900)	(0.00916)
No. of children (aged 0-3)	-0.0793	0.0141	0.0137
	(0.0606)	(0.0114)	(0.0114)
No. of children (aged 3-6)	-0.0483	-0.00299	-0.00274
	(0.0520)	(0.0109)	(0.0109)
No. of children (aged 6-14)	-0.0187	0.0154**	0.0158**
	(0.0370)	(0.00732)	(0.00734)
Married	-0.270***	-0.00303	-0.00873
	(0.0392)	(0.00747)	(0.00855)
Sex	-0.157***	-0.0197***	-0.0219***
	(0.0325)	(0.00603)	(0.00622)
Medium education	-0.0633	0.0212***	0.0198**
	(0.0430)	(0.00766)	(0.00770)
High education	0.0383	0.0827***	0.0823***
	(0.0479)	(0.00905)	(0.00905)
Full time	-0.129***	0.0318***	0.0304***
	(0.0366)	(0.00682)	(0.00696)
Part time	-0.0762*	0.00196	0.000826
	(0.0407)	(0.00763)	(0.00765)
Medium real household income	-0.448***	0.0780***	0.0698***
	(0.0293)	(0.00646)	(0.00882)
High real household income	-0.877***	0.175***	0.156***
	(0.0401)	(0.0107)	(0.0173)
Couple: Migrant	0.377***	-0.000857	0.00596
	(0.0562)	(0.0121)	(0.0132)
Couple: Mix	0.246***	-0.00243	0.00181
	(0.0364)	(0.00693)	(0.00765)
No partner	-0.00396	-0.0410***	-0.0408***
	(0.0505)	(0.0108)	(0.0108)
Partner: Full time	-0.0821**	-0.0235**	-0.0236**
	(0.0415)	(0.00980)	(0.00980)
Partner: Part time	-0.138***	-0.0115	-0.0146
	(0.0415)	(0.0104)	(0.0105)
Urban regions	0.256***	0.137***	0.141***
	(0.0284)	(0.00708)	(0.00769)
Size (sq.m.)		-0.00700***	-0.00697***
		(0.000557)	(0.000558)
Size squared (÷ 1000)		0.0193***	0.0191***
		(0.00321)	(0.00322)
Has cellar		0.0263***	0.0264***
		(0.00904)	(0.00903)
Has garden		-0.0212***	-0.0214***
		(0.00542)	(0.00541)
Has central heating		0.0796***	0.0794***
		(0.0133)	(0.0133)
Has balcony		0.0743***	0.0743***
		(0.00560)	(0.00560)
In good condition		0.0825***	0.0823***
		(0.0128)	(0.0128)
Partial renovation		0.0448***	0.0448***
		(0.0126)	(0.0126)
Year moved into dwelling		0.00313***	0.00314***
		(0.000260)	(0.000260)
Share empty apartments (state level)		0.00176	0.00177
		(0.00466)	(0.00466)
Inverse Mill Ratio, λ_{ijt}			0.0329
			(0.0242)
Federal State FE	yes	yes	yes
Observations	48,133	22,637	22,637
R^2_{adj}		0.285	0.285

Notes.—Indicators for the observation year are included. The constant is not reported. Standard errors are robust to clustering at the household level and are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source.—Authors' calculations based on SOEP, Destatis and RWI-GEO-GRID.

TABLE C.4
RENT PAID

	Model 4 (1)	Model 5 (2)
Number of persons	-0.00266	-0.00191
	(0.00421)	(0.00415)
Age of Individual	-0.00350***	-0.00306***
	(0.00104)	(0.00102)
Age squared (÷ 1000)	0.0415***	0.0384***
	(0.00879)	(0.00863)
No. of children (aged 0-3)	0.0146	0.0157
	(0.0114)	(0.0110)
No. of children (aged 3-6)	0.0000730	0.00127
	(0.0108)	(0.0105)
No. of children (aged 6-14)	0.0140**	0.0130*
	(0.00707)	(0.00695)
Married	-0.00671	-0.00558
	(0.00811)	(0.00790)
Sex	-0.0212***	-0.0202***
	(0.00593)	(0.00585)
Medium education	0.0218***	0.0193***
	(0.00735)	(0.00730)
High education	0.0799***	0.0735***
	(0.00864)	(0.00855)
Full time	0.0243***	0.0237***
	(0.00675)	(0.00668)
Part time	-0.00442	-0.00496
	(0.00725)	(0.00714)
Medium real household income	0.0645***	0.0631***
	(0.00840)	(0.00826)
High real household income	0.145***	0.144***
	(0.0165)	(0.0162)
Couple: Migrant	-0.0120	-0.0109
	(0.0123)	(0.0124)
Couple: Mix	-0.00637	-0.00509
	(0.00722)	(0.00708)
No partner	-0.0466***	-0.0463***
	(0.0103)	(0.0101)
Partner: Full time	-0.0262***	-0.0255***
	(0.00931)	(0.00916)
Partner: Part time	-0.0148	-0.0173*
	(0.0101)	(0.0100)
Size (sq.m.)	-0.00694***	-0.00679***
	(0.000539)	(0.000533)
Size squared (÷ 1000)	0.0190***	0.0183***
	(0.00312)	(0.00308)
Has cellar	0.0247***	0.0232***
	(0.00866)	(0.00848)
Has garden	-0.0165***	-0.0150***
	(0.00518)	(0.00513)
Has central heating	0.0852***	0.0836***
	(0.0131)	(0.0130)
Has balcony	0.0764***	0.0752***
	(0.00536)	(0.00529)
In good Condition	0.0874***	0.0855***
	(0.0124)	(0.0121)
Partial renovation	0.0471***	0.0457***
	(0.0122)	(0.0119)
Year moved into dwelling	0.00324***	0.00328***
	(0.000251)	(0.000249)
Share empty apartments (state level)	0.0112**	0.0114**
	(0.00464)	(0.00461)
Urban regions	0.0949***	0.0707***
	(0.00761)	(0.00769)
Inverse Mill Ratio, λ_{ijt}	0.0188	0.0153
	(0.0231)	(0.0228)
$\overline{\nu}_{jt}$		0.130***
		(0.00942)
Foreigner	1.649***	1.765***
	(0.0790)	(0.0781)
Unemployment rate	-0.0159***	-0.0151***
	(0.000879)	(0.000877)
Federal State	yes	yes
Observations	22,637	22,637
R^2_{adj}	0.325	0.336

NOTES.—Indicators for the observation year are included. The constant is not reported. Standard errors are robust to clustering at the household level and are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE.—Authors' calculations based on SOEP, Destatis and RWI-GEO-GRID.