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Neighborhood Effects and Individual Unemployment

Abstract

Using a unique dataset for Germany that links individual longitudinal data from the GSOEP to regional data from the federal employment agency and data of real estate prices, we evaluate the impact of neighborhood unemployment on individual employment propects. The panel setup and richness of the data allows us to overcome some of the identification problems which are present in this strand of literature. The empirical results indicate that there is a significant negative impact of neighborhood unemployment on the individual employment probability.

JEL Classification: J65, R23

Keywords: Social interactions; unemployment; neighborhood characteristics

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1 Introduction

Agents belonging to the same group tend to behave similarly and to display similar outcomes. A prominent example is the observation that growing up in a higher (socio-)economic status neighborhood and attending a school with (socio-)economically advantaged classmates is often associated with better academic, social, and labor market outcomes. These stylized facts are complemented by the observation of increasing income inequality, a decline in the earnings and employment opportunities of those at the bottom of the income distribution as well as an increase in the regional concentration of poverty and racial segregation. From a policy point of view, residential segregation and its potential impact on the socioeconomic performance and outcomes of individuals (as well as their children) is a highly relevant topic. Inner cities in the US, suburbs of Paris and deprived areas of large German cities like Berlin, are regularly a cause for concern.

In the economic literature, these observations have drawn pronounced attention to models of social interactions (Manski, 2000). Such models refer to direct interactions between individuals that are not mediated by market mechanisms and which lead to similarities in the behavior of individuals belonging to a given reference group.[1] Social interaction models display a variety of interesting features and implications. The interdependence between group behavior and individual behavior may, for instance, lead to multiple equilibria which are all consistent with individual rationality and can include so-called low-level equilibria or "traps". This means, for instance, that in such models a culture of poverty can emerge from which it is hard to escape. Moreover, social interactions may have important repercussions on the effectiveness and efficiency of policy interventions, since specific interaction effects are able to create "social multipliers", i.e. policy interventions can have a positive spill-over effect on non-treated individuals, if they affect their behavior via certain social interactions with treated individuals (see

[1] Models explaining such phenomena carry different names among which social interactions, social learning, social capital, neighborhood effects, preference interdependence, herd behavior, social networks, peer effects and social norms are the most prominent.

Manski, 1993b; Moffitt, 2001; Durlauf, 2004). However, the extent to which the association between individual behavior and/or outcome and the behavior and/or outcome of a given reference group reflects a causal relationship is still debated heavily.

Against this scientific and policy background, this paper investigates the relationship between neighborhoods and individual labor market outcomes. The central questions we address are: Does living in a disadvantageous neighborhood exhibit a detrimental causal impact on the behavior and labor market outcomes of an individual? Or is living in a specific neighborhood the manifestation of a sorting mechanism that is affected by an unobservable factor which also determines labor market outcomes? In particular, we investigate whether the unemployment rate in a neighborhood has a causal impact on the unemployment probability of individuals living in this neighborhood.

To answer these research questions, we employ a unique dataset that links rich longitudinal individual data from the German Socio-Economic Panel (GSOEP) to administrative and regionally aggregated data from the federal unemployment agency as well as house prices obtained from the biggest German internet platform for real estates. To indentify the causal effect of the neighborhood unemployment rate on the individual unemployment probability, we follow a strategy developed by Bayer and Ross (2006), which combines instrumental variable estimators with a control function approach. Our empirical results show that the individual employment probability is negatively affected by the neighborhood unemployment rate, i.e., that an increase in the local unemployment rate by 1 percentage point increases the individual unemployment probability on average by about 1.6%. Hence, our results indicate that social interactions are indeed able to create "social multipliers".

The paper proceeds as follows. In the next section we provide a brief literature review on neighborhood effects, concentrating on studies investigating the effects of neighborhoods on individual employment outcomes. Section

3 describes our data and discusses our empirical strategy. The estimation results are presented in Section 4, while Section 5 summarizes our results and draws some policy conclusions.

2 Literature Review

The existing theoretical literature suggest several channels through which the neighborhood may affect individual employment status: (i) sorting, (ii) interdependencies in the constraints faced by individuals in the same neighborhood, and (iii) social networks.[2] With respect to sorting, neighborhood effects on unemployment may occur just because individuals with similar characteristics may prefer to live in the same neighborhood. Papers that stress the role of interdependencies in individuals' constraints usually argue that a higher aggregate unemployment lowers the psychological costs of unemployment by making this status more of the norm and hence lowers individual search intensity (see, among others, Besley and Coate, 1992; Clark, 2003; Kassenböhmer and Haisken-DeNew, 2009; Lindbeck et al., 1999; Pissarides, 2000). Finally, neighborhoods may affect individual employment status through social networks, which transfer information about job vacancies faster and in a more efficient way and may lead to more job referrals (see, among others, Montgomery, 1990; Finneran and Kelly, 2003; Krauth, 2004).

Empirical studies of neighborhood effects are subject to severe identification problems (see Manski, 1989, 1993a,b, 1995, 2000). For the identification of neighborhood effects, one has to distinguish between endogenous interactions, exogenous or contextual interactions, and correlated effects (Manski, 1993b, 2000). Endogenous interactions in the sense of Manski refer to the propensity that an individuals behavior varies with the behavior of the respective reference group, while exogenous or contextual interactions refer

[2]A comprehensive overview of the neighborhood effects literature is given by Durlauf (2004).

to the possibility that the behavior of individuals is affected by the exogenous characteristics of the reference group. Correlated effects subsume the possibility that the behavior of different individuals belonging to the same reference group is similar just because they have the same characteristics or face the same institutional settings. Typically, disentangling these three different effects is not possible without strong identification assumptions. To discriminate between these three effects is, however, essential because only endogenous interactions are able to create spill-over or feedback effects of policy interventions between treated and non-treated individuals, while contextual interactions and correlated effects do not display such a social multiplier.

Manski (1993b) shows that inference on these different social interaction effects is not possible as long as the researcher has no prior information on the composition of the reference group of an individual. In most empirical studies the reference group is typically assumed without providing further evidence for this choice (one noticeable exception is Woittiez and Kapteyn, 1998). But even if this information were available, identification of specific social effects critically depends on a set of identification assumptions. The main obstacle to identifying different forms of social interactions, which is – following Manski – referred to as the reflection problem, is the fact that the average behavior of the reference group itself is influenced by individual behavior. It is *a priori* not clear from observing the value of a specific outcome measure, whether group behavior impinges upon individual behavior or if the behavior of the group is simply the aggregation of all individual behaviors. Therefore, it is very difficult to separately identify endogenous and contextual effects. Because of this problem, existing empirical studies either just aim to estimate one of the two effects assuming the absence of the other or the aggregate of both effects.

In addition to the reflection problem, it is necessary to disentangle endogenous and contextual effects from correlated effects. The later could be considered as a self-selection problem resulting from the possibility that individuals choose to live in the neighborhood of persons with the same characteristics, some of which may be unobserved to the econometrician (see, e.g. Evans et al., 1992; Rivkin, 2001) or that individuals could value certain unobservable amenities in a neighborhood. In consequence, the conclusions reached by different empirical studies addressing the existence and extent of such neighborhood effects often depend upon the specific identification strategy used to account for the potential endogeneity of neighborhood choice.

The identification of endogenous social interactions and, therefore, their distinction from contextual interactions and correlated effects is the most challenging issue in this research area. It is typically conceived that such effects are most credibly identified by a social experiment, i.e. a randomly assigned social program which operates at different intensities within and between peer groups (see, among others, Duflo and Saez, 2002; Kling et al., 2001; Sacerdote, 2006; Zimmerman, 2003). Randomization secures identification by balancing the treatment and control group in all relevant characteristics, observable as well as unobservable. The majority of empirical research, however, comprises observational studies facing the potential problem of endogeneity of reference group choice. Often, this problem is addressed either by an instrumental variable or by a control function approach. Some studies also restrict their sample to individuals for which one can assume that they did not choose their neighborhood, such as, for example, youths still living with their parents (Dujardin et al., 2009)

Overall, the existing empirical evidence suggests that a deprived neighborhood indeed reduces individual employment prospects. Studies utilizing data from controlled and natural experiments mostly find significant neighborhood effects. The Gautreux Experiment, which started in Chicago in 1976, assigned low-income African-Americans randomly to middle-income white suburbs and low-income urban areas by a quasi-random assignment of destinations via housing vouchers. The empirical results suggest that suburban movers show higher employment probabilities, higher youth educational and better social integration outcomes (Rosenbaum, 1995). The Gautreux Program was the blueprint for the Moving-to-Opportunity Program (MTO), which was conducted in five US cities. Evidence from the MTO randomized experiments in Boston and Baltimore indicate the presence of significant neighborhood effects: various outcome measures (employment, earnings, criminal activity) exhibit improvements of up to 50% compared to the control group of individuals staying in deprived regions (see, among others, Kling et al., 2001; Ludwig et al., 2001; Rosenbaum and Harris, 2001; Oreopoulos, 2003). However, controlled experiments suffer from the problem that their external validity is questionable. Hence, the extent to which their results can be extrapolated to the population not under study is an unresolved issue.

Empirical studies using observational data also predominantly conclude, that neighborhoods matter for individual labor market outcomes. These studies use a variety of different empirical strategies to identify neighborhood effects, including, for example, a combination of fixed-effects to control for correlated effects and an instrumental variable or control function approach to deal with selection effects (see, among others, Bayer and Ross, 2006; Bayer et al., 2008; Bertrand et al., 2000; Case and Katz, 1991; Dujardin and Goffette-Nagot, 2006, 2010; Weinberg et al., 2004). Brock and Durlauf (2001a,b) show that Manski's reflection problem may be solved in non-linear regression models. Empirical studies that are based on non-linear models rather than linear-in-means models also point towards significant neighborhood effects. As a prominent example, van der Klaauw and van Ours (2003) investigate the influence of the neighborhood on the transition rates from welfare to work in Rotterdam. They estimate Mixed Proportional Hazard Rate models controlling for a variety of neighborhood characteristics, such as the local unemployment rate and average house prices, as well as neighborhood fixed effects. They find a negative relationship between the neighborhood unemployment rate and the transition rate from welfare to work for young Dutch, but not for older and non-Dutch welfare recipients. This result confirms similar empirical studies of neighborhood effects for the US (Hoynes, 2000) and Sweden (Hedström et al., 2003).

3 Identification Strategy and Data

The following basic empirical model, which resembles the standard linear-in-means model of neighborhood peer effects (Manski, 1993a; Case and Katz, 1991), is our starting point to evaluate the effect of neighborhood unemployment on individual unemployment:

$$\begin{aligned} Y_{ijt} &= \alpha + \beta X_{ijt} + \gamma N_{jt} + \varepsilon_{ijt} \\ &= \alpha + \beta X_{ijt} + \theta \bar{U}_{jt} + \eta Z_{jt} + \psi_i + \tau_j + \delta_t + u_{ijt}, \end{aligned} \tag{1}$$

where Y_{ijt} is a discrete variable taking the value 1 if an individual i, living in the neighborhood j is unemployed at time t, and 0 otherwise. We assume that the relevant neighborhood for an individual is defined by the postal area, as these areas are smaller than most existing official boundaries and often bounded by distinct landmarks, e.g. major roads encircling an area or certain parts of a town. Furthermore postcodes are visible to the individual as well as to the outside world, thus allowing for the presence of stigma or status effects. Additionally, they are still small enough to allow their use as a neighborhood. X_{ijt} is a vector of observable individual characteristics, including a squared function of age, indicator variables for marriage status, foreigner status, and gender, as well as two dummy variables for the educational degree of the individual. $N_{jt} = \bar{U}_{jt} + Z_{jt}$ captures observable average neighborhood characteristics consisting of the average unemployment rate in the neighborhood $\bar{U}_{jt}$ and other observable neighborhood characteristics Z_{jt}. The error term $\varepsilon_{ijt} = \psi_i + \tau_j + \delta_t + u_{ijt}$ is assumed to capture unobserved individual characteristics ψ_i, unobserved neighborhood characteristics τ_j, unobserved shocks to the neighborhood δ_t and an idiosyncratic error u_{ijt}.

The main coefficient of interest is θ, which – following Manskis' terminology – captures the endogenous effect of unemployment in the neighborhood on the individual unemployment propensity. Even though we control for a number of personal and neighborhood characteristics, this parameter may still be biased, since it is likely to capture a mixture of endogenous, correlated and contextual effects (Manski, 1993b, 1995). We aim to control for contextual effects by including a set of neighborhood control variables in the vector $\bar{Z}_{jt}$, i.e. the share of foreigners, the number of individuals living in the area and average education proxied by the share of higher educated workers living in the area. Correlated effects, that is exogenous shocks which happen to affect all individuals belonging to a peer group (in this case also living in the same neighborhood), are most likely controlled for by including time fixed effects (δ_t) in the model (Bertrand et al., 2000; Fletcher, 2010).

Even though our data allows us to control for a number of individual and neighborhood characteristics, our estimates may still be biased because unobserved individual and neighborhood characteristics may be correlated with the neighborhood characteristics N_{jt}, i.e. because $cov\left(N_{jt}, \psi_i\right) \neq 0$ and $cov\left(N_{jt}, \tau_j\right) \neq 0$. The former may happen because individuals sort themselves non-randomly over neighborhoods and thereby generate a correlation between the unemployment rate in the neighborhood and unobservable individual characteristics. For example, ambition may drive the sorting process into different neighborhoods. Second, unobserved neighborhood characteristics, such as, e.g. an inefficient employment agency, may be correlated with the observed mean unemployment rate in the neighborhood. To eliminate the bias arising from these correlations, we follow a two step procedure that follows the identification strategy outlined by Bayer and Ross (2006). To control for the correlation between individual unobservables and neighborhood characteristics we rely on an instrumental variable approach (IV). The potential bias of θ that may arise through the correlation between unobserved and observed neighborhood characteristics is addressed by a control function approach.[3]

The IV method to control for individuals sorting on unobservable charac-

[3]Using a control function approach to address a potential bias due to unobserved neighborhood characteristics has also been suggested by Ioannides and Zabel (2008) and Brock and Durlauf (2007).

teristics is implemented as a cell-based approach. We take all permutations of observable individual characteristics, i.e. age (aggregated to five-year brackets), gender, marital status, nationality and three education level categories, to generate cells of observably identical individuals. The cell means of the neighborhood characteristics over these observably identical individuals are then used as instruments for the neighborhood characteristics captured by the vector N_{jt} in equation (1).[4] Hence, we eliminate the portion of variation in neighborhood characteristics which is due to sorting on individual unobservables and use only the portion of variation that is explained by observable individual characteristics. This implies, that we expect observationally identical individuals as being exposed to similar neighborhood characteristics. Note that this IV approach is equivalent to a fully specified non-parametric sorting model (Bayer and Ross, 2006). The non-linearity of this approach should further facilitate the identification of peer effects (Brock and Durlauf, 2001a,b; Durlauf, 2001).

The second part of our identification strategy involves obtaining a measure for unobservable neighborhood characteristics τ_j using a control function approach. Again, we follow Bayer and Ross (2006) and take the average regional residual from a hedonic house price regression, which includes neighborhood characteristics as well as controls for the particular dwelling:

$$\log\left(P_{kjt}\right) = \xi + \phi H_{kjt} + \zeta N_{kjt} + \omega_{kjt}, \tag{2}$$

where P_{kjt} is the price of house k in the postal area j at time t. H_{kjt} are house characteristics (size, number of rooms, a cubic function of the age of the dwelling, type of dwelling and dummies controlling for the quality of the dwelling), and N_{kjt} are the regional characteristics described above.[5] We use the average residual $\bar{\omega}_{jt}$ calculated over each postal area from equation (2) as an additional control variable in equation (1). The residual from equation (2)

[4] The cell-means are calculated without the individual contribution to the mean. As a robustness check we excluded cells with fewer than five observations. The results reported below, however, are insensitive towards this exclusion.

[5] The results from estimating equation (2) are reported in Appendix-Table 6.

should capture all factors influencing the house price besides the observable characteristics of the individual building and neighborhood. Hence, $\bar{\omega}_{jt}$ can be interpreted as a factor controlling for unobservable regional amenities, for which individuals are inclined to pay more. This is a reasonable control function approach, as long as individuals sort into neighborhoods with regard to income and housing quality and/or amenities.[6]

Figure 1: Residual from Hedonic House Price Regression

The regional distribution of residuals from the hedonic house price regression, i.e. $\bar{\omega}_{jt}$, is shown in Figure (1), with darker dots indicating postal areas in which individuals are willing to pay more to live than the amount

[6]We also estimated equation (2) using an instrumental strategy similar to the one used above in the individual unemployment regression model, where we instrument the neigborhood characteristics with cell means based on all permutations of observable house price characteristics. This ensures, that the typical characteristics of houses, i.e. overall housing quality, in a neighborhood is not affected by observed neighborhood characteristics, which would lead to reverse causation problem. Both approaches, however, yield similar results. Hence, we report only those results obtained by estimating equation (2) by OLS. The estimation results from the IV approach are available from the authors upon request.

attributable to observed housing and neighborhood characteristics. The figure shows that the most expensive areas are around Munich in the South, Frankfurt, the area around Cologne, Hamburg, and Berlin, while $\bar{\omega}_{jt}$ is relatively low in the rural areas of Germany.

A final problem emerges, as $\bar{\omega}_{jt}$ may well be correlated with ψ_i because individuals could have unobservably different preferences for these neighborhood amenities. We overcome this problem by using an instrumentation strategy as before, with the the cell means of $\bar{\omega}_{jt}$ for observationally identical individuals as instruments.

Hence, the most elaborated model we estimate is

$$y_{ijt} = \alpha + \beta X_{ijt} + \gamma \hat{Z}_{jt} + \theta \hat{\hat{U}}_{jt} + \hat{\bar{\omega}}_{jt} + \varepsilon_{ijt}, \tag{3}$$

with Z_{jt}, U_{jt} and $\bar{\omega}$ as instrumented variables. Neighborhood characteristics and the control for unobservable neighborhood characteristics in this specification are purged of any influence from sorting behavior (i.e. the sorting on unobservables), giving us an unbiased estimator of the effect of neighborhood unemployment on the individual unemployment probability θ.

The data used to estimate equation (3) is a unique dataset comprised of three parts: longitudinal individual data from the German Socioeconomic Panel (SOEP)[7], information on house prices and house characteristics obtained from an online real estate agency platform, and administrative labor force data provided by the Research Data Centre of the Federal Employment Agency at the Institute for Employment Research. The latter is taken from the official employment and unemployment registers[8] and provides information on the employment status, the nationality, age, and gender for

[7]The data extraction from the SOEP was done using PanelWhiz (Haisken-DeNew and Hahn, 2010)

[8]This data is part of the SOEP Neighborhood Project at the RWI. The authors want to thank Stefan Bender and Jörg Heining from the Research Data Centre at the Federal Employment Agency for their invaluable effort and support and the Leibniz-Gemeinschaft for financial support.

all persons officially registered as unemployed or employed and liable to the social security system.[9] Note that the this administrative data provides information on the education level only for employed persons. Hence, the the corresponding shares used in the empirical analysis refers to the educational status of the workforce. The individual level data from the GSOEP contains individual information on age, education, marital status, gender and nationality. The data on house prices was obtained from *Immobilienscout 24*, which is the largest German online platform for selling and renting houses and flats. This dataset contains all recorded offers from the years 2003 to 2004 and includes information on house characteristics as well as the offering price and can be merged to the other data sources on the postcode level.

Using the employment registers, we calculate the size of the workforce as the sum of employed persons who are subject to social insurance contributions and registered unemployed persons. We also include the share of workers with higher education (i.e. with a university degree or a degree from a university of applied science), the share of foreigners in the workforce as well as the share of unemployed at the postcode level for the period from 2003 to 2004. Due to data quality issues we are not able to extend our analysis past 2004. In 2005 the new unemployment benefit system in Germany (commmonly known as "Hartz IV-reform") was implemented. This reform resulted in severe data problems in the following years, as unemployment data was not properly exchanged between local and federal unemployment agencies. This generated data from the employment statistics has then been merged to the SOEP on the level of 3,032 distinct postcode areas. The following empirical analysis is further restricted to all individuals aged between 17 and 65 not in full time education, resulting in an unbalanced panel of 21,237 person-year observations of 12,932 individuals for the years 2003 and 2004.

[9] Not covered are therefore unemployed persons who are not registered as unemployed, employed persons in minor employment or in employment outside the general social security system, mainly self-employed and government workers.

Table 1 provides unweighted descriptive statistics of the variables used in the empirical analysis. It appears that the average individual unemployment probability is 9.8%, while the average unemployment share in the neighborhood is about 12%. Several factors may be responsible for this difference. First, the SOEP is neither representative for the German population nor for those who have paid social security contributions, the latter being the population of the employment registers. Second, the data from the SOEP is usually collected in the first three months of a year, while the unemployment rate from the employment registers have been calculated using end-of-the-year notifications and third, the individual unemployment information is self-reported and not necessarily identical to the official unemployment definition. For similar reasons the local share of long-term unemployment, defined as the number of unemployed with an unemployment spell longer than one year, of 2.8% differs from the individual probability of being unemployed for more than a year. Also the share of foreigners in the SOEP differs from the respective share obtained from the employment registers. While about 14% of the individuals in our sample are foreigners, the average share of foreigners in the neighborhood is 7.3%. Again the non-representativeness of the SOEP is responsible for the this divergence, since the SOEP oversamples foreigners. Another reason, why the numbers diverge between both datasets is the relatively high proportion of foreigners in self-employment (Sachverständigenrat deutscher Stiftungen für Integration und Migration, 2010).

We use the ISCED classification to control for an individuals' level of education. The lowest ISCED levels 1-2 (and below) comprise basic schooling and lower secondary schooling. Henceforth, we refer to this group as low-educated. ISCED 3-4 refers to medium educated individuals, i.e. persons with upper secondary schooling and any post-secondary schooling as well as vocational training in combination with basic schooling. ISCED 5-6 refers to tertiary education and higher education in general. The share of lower educated persons in our sample is about 18%, medium educated individuals make up 59% and the highest educated group comprises about 23%. In our

Table 1: Descriptive Statistics

	2003		2004		Overall	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Individual Variables						
Age	41.131	11.837	42.109	11.899	41.652	11.880
(within-variation)						(12.201)
(between-variation)						(0.442)
Age^2 (1,000)	1.832	0.974	1.915	0.989	1.876	0.983
						(1.007)
						(0.038)
Married	0.019	0.137	0.017	0.13	0.018	0.133
						(0.126)
						(0.072)
Foreigner	0.142	0.349	0.131	0.338	0.136	0.343
						(0.338)
						(-)
Female	0.471	0.499	0.472	0.499	0.472	0.499
						(0.499)
						(-)
Low Education (ISCED 1-2)	0.174	0.379	0.156	0.362	0.164	0.370
						(0.370)
						(0.041)
Medium Education (ISCED 3-4)	0.615	0.487	0.59	0.492	0.602	0.490
						(0.490)
						(0.045)
High Education (ISCED 5-6)	0.211	0.408	0.254	0.436	0.234	0.424
						(0.430)
						(0.019)
Unemployed	0.098	0.298	0.098	0.297	0.098	0.297
						(0.285)
						(0.115)
Neighborhood Variables						
Local Unemployment Rate (%)	12.331	6.12	11.941	5.738	11.301	5.501
						(5.537)
						(0.402)
Local Long-Term Unemployment Rate (%)	2.887	1.524	2.552	1.508	2.745	1.517
						(1.115)
						(0.686)
Population (1,000)	7.857	4.437	7.874	4.414	6.944	3.971
						(3.930)
						(0.080)
Share of Highly Educated (%)	7.812	4.921	7.959	5.184	7.992	5.466
						(5.609)
						(0.507)
Share of Foreigners (%)	7.272	7.659	7.338	7.717	7.723	7.826
						(7.870)
						(0.428)

Note: Number of Observations: 9,920 (2003); 11,317 (2004) empirical analysis, we use the lowest skilled group as the control group.

On average 7,900 individuals are living in a typical postal code area. The smallest neighborhood has a population of about 2,500 persons, the largest of almost 25,500. The share of workers with a tertiary schooling degree in a neighborhood is on average 7.9% varying from 0% to more than 40%. Also the share of foreigners in a neighborhood shows a high variation. On average this share is 7.3% varying from 0% to almost 49%. The same holds for the share of unemployed, which varies between 3.1% and 38.9%.

4 Results

Table 2 shows the basic results from estimating equation (3) by OLS to provide a documentation of the multivariate correlatione between the individual unemployment probability and the local unemployment rate. In column (1) we only control for individual characteristics in addition to the regional unemployment rate and a time fixed effect, adding neighborhood controls to the specification in column (2) and our measure for the unobservable neighborhood quality obtained from the estimated hedonic house price equation (2) in column (3). The estimated correlation of the unemployment rate in the neighborhood on the individual unemployment probability is positive and highly significant in all three specifications. However, even if one would be able to interpret these coefficients as a causal relationship, they would not necessarily hint towards the existence of neighborhood effects. Assume that the average individual unemployment probability is the same as the mean local unemployment rate. Then a shock that increases the individual unemployment probability should increase the local unemployment rate by the same amount, i.e. the coefficient of the local unemployment rate is expected to be 0.01. Due to the reasons discussed above, the average individual unemployment rate is not equal to the local unemployment rate in our sample. Therefore, in the absence of neighborhood effects we would expect a coefficient of 0.0081 (= 0.098 /12.1) for the local unemployment rate. Since the estimated coefficients on the unemployment rate in the neighborhood are significantly larger than 0.0081, the results shown in Table 2 indeed suggest that neighborhoods might matter.

The estimated coefficients for the individual control variables are as expected. We find an U-shaped effect of age, a higher unemployment probability for foreigners and a pronounced lower unemployment probability for high skilled individuals. The neighborhood controls for the population size in the postcode area, the share of foreigners and the share of high skilled workers are insignificant and close to zero in magnitude. The coefficient of our neighborhood quality control variable $\bar{\omega}_{jt}$ is negative, but insignificant. Note further, that neither the inclusion of observable neighborhood characteristics nor the inclusion of $\bar{\omega}_{jt}$ has a significant impact on the estimated effect of the local unemployment rate on the individual unemployment probability, indicating that in our case contextual effects do not bias the estimated effect of interest.

The OLS estimates of neighborhood effects shown in Table 2 may still be biased due to the sorting behavior of individuals with respect to neighborhood characteristics and unobservable neighborhood quality. We therefore turn our focus to the estimated effects of the local unemployment rate on the individual unemployment probability obtained from our IV regressions, which are summarized in Table 3.[10] Column (1) of Table 3 refers to the most simple IV specification where neighborhood unemployment and all other neighborhood controls are instrumented by the cell means of observationally identical individuals. Column (2) adds our control variable for neighborhood quality, and in column (3) the latter is also instrumented in the same way as all other neighborhood characteristics. The estimated coefficients reported in column (3) provide unbiased estimates for all neighborhood variables as long as individuals sort themselves over neighborhoods with respect to their income.

[10]The estimation results for all variables can be found in Appendix-Table 7.

Table 2: Individual Unemployment and Neighborhood Unemployment: OLS Estimates

	(1)	(2)	(3)
Age	-0.0048^{***}	-0.0048^{***}	-0.0048^{***}
	(0.0013)	(0.0013)	(0.0013)
Age^2 (1,000)	0.0835^{***}	0.0840^{***}	0.0843^{***}
	(0.0167)	(0.0168)	(0.0168)
Married	0.0384^{**}	0.0386^{**}	0.0387^{**}
	(0.0165)	(0.0165)	(0.0165)
Foreigner	0.0635^{***}	0.0654^{***}	0.0653^{***}
	(0.0085)	(0.0086)	(0.0086)
Female	-0.0034	-0.0034	-0.0034
	(0.0047)	(0.0047)	(0.0047)
Medium Education (ISCED 3-4)	-0.0336^{***}	-0.0340^{***}	-0.0340^{***}
	(0.0082)	(0.0082)	(0.0082)
High Education (ISCED 5-6)	-0.1252^{***}	-0.1258^{***}	-0.1258^{***}
	(0.0094)	(0.0095)	(0.0095)
Year 2003	-0.0067^{**}	-0.0067^{**}	-0.0064^{**}
	(0.0031)	(0.0031)	(0.0031)
Local Unemployment Rate	0.0100^{***}	0.0097^{***}	0.0097^{***}
	(0.0005)	(0.0006)	(0.0006)
Population (1,000)		0.0008	0.0009
		(0.0006)	(0.0006)
Share of Highly Educated		-0.0001	-0.0002
		(0.0005)	(0.0005)
Share of Foreigners		-0.0006	-0.0004
		(0.0004)	(0.0004)
$\bar{\omega}_{jt}$			-0.0092
			(0.0097)
Constant	0.0642^{**}	0.0665^{**}	0.0658^{**}
	(0.0259)	(0.0270)	(0.0270)
R^2	0.0543	0.0544	0.0544

Note: 21,237 observations. Standard errors in parentheses
Standard errors are robust and clustered on postal area
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Individual Unemployment and Neighborhood Unemployment: IV Estimates

	(1)	(2)	(3)
Local Unemployment Rate	0.0158**	0.0141*	0.0162**
	(0.0080)	(0.0083)	(0.0074)
Population (1,000)	0.0076	0.0108	0.0067
	(0.0285)	(0.0288)	(0.0278)
Share of Highly Educated	0.0017	−0.0028	0.0029
	(0.0158)	(0.0176)	(0.0175)
Share of Foreigners	0.0107	0.0129	0.0101
	(0.0085)	(0.0097)	(0.0102)
$\bar{\omega}_{jt}$		−0.1630	0.0418
		(0.1042)	(0.1802)
R^2	0.0516	0.0288	0.0475
First Stage Statistics			
Local Unemployment Rate:			
Shea-Partial R^2	0.0596	0.0598	0.0618
F-Statistic (1^{st})	18.554	21.396	15.302
Population:			
Shea-Partial R^2	0.0084	0.0080	0.0084
F-Statistic (1^{st})	14.919	15.171	12.039
Share of Highly Educated:			
Shea-Partial R^2	0.0111	0.0092	0.0098
F-Statistic (1^{st})	13.636	13.120	11.189
Share of Foreigners:			
Shea-Partial R^2	0.0313	0.0287	0.0290
F-Statistic (1^{st})	23.579	23.908	25.736
$\bar{\omega}_{jt}$:			
Shea-Partial R^2			0.0685
F-Statistic (1^{st})			158.02

Note: 21,237 observations. Standard Errors in parentheses. The regression models further control for the age and age squared and the marital status of the individuals, a dummy variable for foreigner status, two dummy variables for the educational degree and a dummy for the year 2003. See Appendix-Table 7 for full results.
Standard errors are robust and clustered on cells (198 cells)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For all specifications, Table 3 shows significantly positive effects of the share of unemployed in the neighborhood on the individual unemployment probability. The point estimates are larger than the ones obtained when using OLS regressions, indicating that sorting behavior, if not properly controlled for, induces a downward bias in the estimates of peer effects of unemployment. According to the estimated effect in the last column of Table 3, a 1 percentage point increase in the share of unemployed in the neighborhood increases the the individual unemployment probability by around 1.6%.[11] Similar to the OLS model, the estimated effects of the other neighborhood variables are neither significant nor does their inclusion affect the estimated effect of the local unemployment rate on the individual unemployment probability. This shows again, that biased estimates due to contextual effects appears not to be of importance for the question at hand. Note finally, that the usual statistics for IV estimates indicate that our estimates do not suffer from a weak instrument problem.

Whether the effect of the local unemployment rate on an individuals' unemployment probability varies for individuals with a different educational background is investigated by interacting the local unemployment rate with the dummy variables indicating the highest schooling degree obtained by an individual. The point estimates from this variation of our specification, which are shown in Table 4, indicate that the effect of the local unemployment rate on the unemployment probability of an individual is lower for both, the medium and the high educated if compared to the group of low educated individuals. However, only the coefficient for the group of highly educated is statistically significant at conventional levels in the OLS model and turns insignificant in the most elaborated IV-model.

Finally, we analyze whether the estimated neighborhood effects differ when using the share of long-term unemployed instead of the overall unemployment in a postcode area. We expect that the effect of the local long-term

[11]Test statistics, showing that the results are significantly different from 0.0081 can be found in the Appendix-Table 15

Table 4: Neighborhood Effects of Unemployment and Education

	OLS	IV
Local Unemployment Rate	0.0104***	0.0205**
	(0.0016)	(0.0100)
Local Unemployment Rate x Medium Education	0.0010	−0.0007
	(0.0017)	(0.0093)
Local Unemployment Rate x High Education	−0.0055***	−0.0105
	(0.0018)	(0.0091)
$\bar{\omega}_{jt}$	−0.0079	0.0104
	(0.0097)	(0.1849)
R^2	0.0572	0.0151

21,237 observations; Standard errors in parentheses
Standard errors are robust and clustered on postal area
See Appendix-Tables 8-11 for full results.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
See also notes to Table 5.

unemployment rate on the individual unemployment probability should be larger than the respective effect of the overall local unemployment rate, if the neighborhood effect is mainly driven by unemployment becoming the social norm or through a lack of social networks. Table 5 shows that the neighborhood effects of long-term unemployment are indeed substantially larger than those obtained when using the overall local unemployment rate.

5 Conclusion

Using a unique data set that combines information from an individual survey with information from administrative social security data and real estate information from an internet platform, we investigate the effect of neighborhood characteristics, especially unemployment in a postcode area, on the individual unemployment probability. To address the various identification problems inherent in the analysis of neighborhood effects, we follow an identification strategy that combines an control function approach with an IV-strategy.

Table 5: Neighborhood Effects of Long-Term Unemployment on Individual Unemployment Probability

	OLS	**IV**
Local Long-Term Unemployment Rate	0.0423***	0.1995**
	(0.0026)	(0.0959)
$\bar{\omega}_{jt}$	−0.0190*	0.0566
	(0.0099)	(0.2044)
R^2	0.0479	0.026

Note: 21,237 observations. Standard errors statistics in parentheses The regression models further control for the age and age squared and the marital status of the individuals, a dummy variable for foreigner status, two dummy variables for the educational degree and a dummy for the year 2003, as well as the size of the population, the share of highly educated and the share of foreigners in the postcode area. See Appendix-Table 12-14 for full results.
Standard errors are robust and clustered on cells (198 cells)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The empirical result indicate that there is a significant and negative causal effect of local unemployment on an individuals' employment probability. According to our estimates, an increase in the local unemployment rate by 1 percentage point increases the individual unemployment probability on average by roughly 1.6%. While these neighborhood effects appear not to vary with the educational background of the individuals, the neighborhood effects are substantially higher when using the long-term unemployment rate instead of the overall local unemployment rate in a postcode area.

From a policy perspective the mere existence of neighborhood effects merit some attention. As we identify endogenous neighborhood effects our results suggest that regional shocks and policy interventions are able to create social multipliers, i.e. spill-over effects on non-treated individuals. One example for such a regional shock is the closure of big companies which draw a big part of their workforce from close surroundings, like in old industrial areas such as the rust belt in the US, the British Midlands or the Ruhr area in Germany. According to our estimates these shocks increase unemployment by more than just the workers who loose their job because of the closing of a company.

The results, however, also imply that policy interventions can exert social multiplier effects. This provides some scope for promising innovative interventions into the labor market. Many labor market authorities throughout Europe provide financial incentives to foster mobility of unemployed to take up a job in another region of the country. Such incentives, however, are usually tied to a concrete job offer in the new region. Our results imply that the unconditional provision of incentives for unemployed to relocate to a region (or part of the city) with a lower incidence of unemployment might help them to find a job via spill-over-effects from their (then better) environment.

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6 Appendix

Table 6: Hedonic House Price Regression

	(1)
Age	-0.000148
	(0.000213)
Age^2 (1,000)	-0.0674^{***}
	(0.00464)
Age^3 (1,000)	0.000310^{***}
	(0.0000278)
log(Size)	0.848^{***}
	(0.00257)
State: Renovated	0.0654^{***}
	(0.00438)
State: Modernized, well-kept	0.00490
	(0.00307)
State: Not Renovated or not stated	0.00341
	(0.00270)
Type: Multi-storey	-0.105^{***}
	(0.00417)
Type: Farmhouse, Bungalow, Villa, Special	0.197^{***}
	(0.00327)
Type: Terrace, Terrace-middle	-0.0536^{***}
	(0.00270)
Type: Terrace-end	-0.0644
	(0.105)
Type: Other	0.0155^{***}
	(0.00251)
Rented Out	-0.170^{***}
	(0.00438)
Year 2004	0.00559^{***}
	(0.00188)
Share of Foreigners	0.00104^{***}
	(0.0000514)
Unemployment Rate	-0.0223^{***}
	(0.000226)
Size (1,000)	0.00134^{***}
	(0.000202)
High Education Share	0.0350^{***}

	(0.000167)
Constant	8.151***
	(0.0136)
R^2	0.589
F-Statistic	13945.4

Note: 174,948 observations. Standard errors in parentheses
Reference categories are: State: New and like New, Type: Single-detached
Standard errors are robust and clustered on postal area
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Individual Unemployment and Neighborhood Unemployment: IV Estimates

	(1)	(2)	(3)
Age	-0.0047^{*}	-0.0055^{*}	-0.0045
	(0.0028)	(0.0030)	(0.0031)
Age^2 (1,000)	0.0846^{***}	0.0949^{***}	0.0820^{**}
	(0.0328)	(0.0359)	(0.0375)
Married	0.0303^{*}	0.0305^{*}	0.0303^{*}
	(0.0169)	(0.0170)	(0.0169)
Foreigner	0.0154	0.0133	0.0159
	(0.0335)	(0.0355)	(0.0344)
Female	-0.0033	-0.0016	-0.0037
	(0.0067)	(0.0072)	(0.0072)
Medium Education (ISCED 3-4)	-0.0267	-0.0246	-0.0272
	(0.0177)	(0.0189)	(0.0186)
High Education (ISCED 5-6)	-0.1283^{***}	-0.1215^{***}	-0.1300^{***}
	(0.0404)	(0.0441)	(0.0430)
Year 2003	-0.0075	-0.0031	-0.0086
	(0.0052)	(0.0063)	(0.0065)
Local Unemployment Rate	0.0158^{**}	0.0141^{*}	0.0162^{**}
	(0.0080)	(0.0083)	(0.0074)
Population (1,000)	0.0076	0.0108	0.0067
	(0.0285)	(0.0288)	(0.0278)
Share of Highly Educated	0.0017	-0.0028	0.0029
	(0.0158)	(0.0176)	(0.0175)
Share of Foreigners	0.0107	0.0129	0.0101
	(0.0085)	(0.0097)	(0.0102)
$\bar{\omega}_{jt}$		-0.1630	0.0418
		(0.1042)	(0.1802)
Constant	-0.1579	-0.1503	-0.1598
	(0.1262)	(0.1274)	(0.1271)
R^2	0.0516	0.0288	0.0475

Note: 21,237 observations. Standard errors in parentheses

Standard errors are robust and clustered on cells (198 cells)

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

Table 8: Neighborhood Effects of Unemployment and Education: OLS Models

	(1)	(2)	(3)
Age	−0.0042***	−0.0043***	−0.0043***
	(0.0014)	(0.0014)	(0.0014)
Age^2 (1,000)	0.0761***	0.0766***	0.0769***
	(0.0170)	(0.0171)	(0.0171)
Married	0.0329**	0.0332**	0.0332**
	(0.0166)	(0.0166)	(0.0166)
Foreigner	0.0608***	0.0630***	0.0629***
	(0.0086)	(0.0086)	(0.0086)
Female	−0.0019	−0.0020	−0.0019
	(0.0047)	(0.0047)	(0.0047)
ISCED 3-4	−0.0475**	−0.0466**	−0.0466**
	(0.0186)	(0.0186)	(0.0186)
ISCED 5-6	−0.0527**	−0.0513**	−0.0516**
	(0.0209)	(0.0208)	(0.0208)
Year 2003	−0.0058*	−0.0058*	−0.0056*
	(0.0031)	(0.0031)	(0.0031)
Local Unemployment Rate	0.0106***	0.0104***	0.0104***
	(0.0016)	(0.0016)	(0.0016)
Medium x Unemp. Rate	0.0011	0.0010	0.0010
	(0.0017)	(0.0017)	(0.0017)
High x Unemp. Rate	−0.0054***	−0.0055***	−0.0055***
	(0.0018)	(0.0018)	(0.0018)
Population (1,000)		0.0007	0.0008
		(0.0006)	(0.0006)
Share of Highly Educated		−0.0002	−0.0003
		(0.0005)	(0.0005)
Share of Foreigners		−0.0006*	−0.0005
		(0.0004)	(0.0004)
$\bar{\omega}_{jt}$			−0.0079
			(0.0097)
Constant	0.0487	0.0522	0.0517
	(0.0314)	(0.0323)	(0.0323)
R^2	0.0571	0.0572	0.0572

Note: 21,237 observations; Standard errors in parentheses
Standard errors are robust and clustered on postal area
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Neighborhood Effects of Unemployment and Education: IV Models

	(1)	(2)	(3)
Age	−0.0028	−0.0037	−0.0028
	(0.0032)	(0.0035)	(0.0035)
Age^2 (1,000)	0.0611	0.0727*	0.0603
	(0.0379)	(0.0416)	(0.0425)
Married	0.0223	0.0229	0.0222
	(0.0164)	(0.0161)	(0.0163)
Foreigner	0.0105	0.0092	0.0106
	(0.0329)	(0.0337)	(0.0335)
Female	−0.0018	−0.0002	−0.0019
	(0.0068)	(0.0071)	(0.0073)
ISCED 3-4	−0.0262	−0.0317	−0.0259
	(0.1042)	(0.1034)	(0.1032)
ISCED 5-6	−0.0097	−0.0142	−0.0094
	(0.0928)	(0.0924)	(0.0917)
Year 2003	−0.0062	−0.0021	−0.0065
	(0.0050)	(0.0058)	(0.0063)
Local Unemployment Rate	0.0203*	0.0180	0.0205**
	(0.0110)	(0.0112)	(0.0100)
Medium x Unemp. Rate	−0.0007	−0.0000	−0.0007
	(0.0094)	(0.0094)	(0.0093)
High x Unemp. Rate	−0.0104	−0.0094	−0.0105
	(0.0092)	(0.0094)	(0.0091)
Population (1,000)	0.0006	0.0043	0.0004
	(0.0285)	(0.0289)	(0.0276)
Share of Highly Educated	0.0092	0.0043	0.0095
	(0.0184)	(0.0201)	(0.0199)
Share of Foreigners	0.0126	0.0146	0.0125
	(0.0085)	(0.0095)	(0.0102)
$\bar{\omega}_{jt}$		−0.1583	0.0104
		(0.1045)	(0.1849)
Constant	−0.2564	−0.2375	−0.2577
	(0.1967)	(0.1971)	(0.1958)
R^2	0.0169	0.0211	0.0151

Note: 21,237 observations; Standard errors in parentheses
Standard errors are robust and clustered on cells (198 cells)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: First Stage Statistics of IV Models in Table 7

	Endogenous Variable				
	Unemployment Share	Population Size	Education Share	Foreigner Share	$\bar{\omega}_{jt}$
IV Model 1					
Shea-Partial R^2	0.0596	0.0084	0.0111	0.0313	
F-Statistic (1^{st})	18.554	14.919	13.636	23.579	
IV Model 2					
Shea-Partial R^2	0.0598	0.008	0.0092	0.0287	
F-Statistic (1^{st})	21.396	15.171	13.12	23.908	
IV Model 3					
Shea-Partial R^2	0.0618	0.0084	0.0098	0.029	0.0685
F-Statistic (1^{st})	15.302	12.039	11.189	25.736	158.02

Table 11: First Stage Statistics for IV Models in Table 9

	UR	**UR x Med**	**UR x High**	**Population**	**Education Share**	**Foreigner Share**	$\bar{\omega}_{jt}$
Interaction IV Model 1							
Shea-Partial R^2	0.2585	0.3941	0.4245	0.0077	0.0091	0.0316	
F-Statistic (1^{st})	18.114	653.369	14.327	10.161	10.954	16.165	
Interaction IV Model 2							
Shea-Partial R^2	0.249	0.3977	0.4116	0.0072	0.0076	0.03	
F-Statistic (1^{st})	20.253	413.2	14.947	10.35	10.652	16.494	
Interaction IV Model 3							
Shea-Partial R^2	0.2663	0.3954	0.4258	0.0077	0.0083	0.0301	0.0712
F-Statistic (1^{st})	16.069	569.736	12.777	8.812	9.852	18.182	112.353

Table 12: Neighborhood Effects of Long-Term Unemployment: OLS Models

	(1)	(2)	(3)
Age	-0.0045^{***}	-0.0047^{***}	-0.0047^{***}
	(0.0013)	(0.0014)	(0.0014)
Age^2 (1,000)	0.0788^{***}	0.0803^{***}	0.0811^{***}
	(0.0168)	(0.0169)	(0.0169)
Married	0.0352^{**}	0.0360^{**}	0.0361^{**}
	(0.0166)	(0.0166)	(0.0166)
Foreigner	0.0567^{***}	0.0606^{***}	0.0606^{***}
	(0.0085)	(0.0087)	(0.0087)
Female	-0.0032	-0.0032	-0.0030
	(0.0047)	(0.0047)	(0.0047)
Medium Education (ISCED 3-4)	-0.0343^{***}	-0.0343^{***}	-0.0343^{***}
	(0.0083)	(0.0082)	(0.0082)
High Education (ISCED 5-6)	-0.1219^{***}	-0.1204^{***}	-0.1206^{***}
	(0.0094)	(0.0095)	(0.0095)
Year 2003	-0.0613^{***}	-0.0599^{***}	-0.0589^{***}
	(0.0045)	(0.0046)	(0.0047)
Local LTU Rate	0.0439^{***}	0.0426^{***}	0.0423^{***}
	(0.0025)	(0.0026)	(0.0026)
Population (1,000)		0.0003	0.0004
		(0.0006)	(0.0006)
Share of Highly Educated		-0.0011^{**}	-0.0012^{**}
		(0.0005)	(0.0005)
Share of Foreigners		-0.0009^{**}	-0.0005
		(0.0004)	(0.0004)
$\bar{\omega}_{jt}$			-0.0190^{*}
			(0.0099)
Constant	0.1153^{***}	0.1308^{***}	0.1285^{***}
	(0.0253)	(0.0262)	(0.0262)
R^2	0.0470	0.0476	0.0479

Note: 21,237 observations; Standard errors in parentheses
Standard errors are robust and clustered on postal area.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Neighborhood Effects of Long-Term Unemployment: IV Models

	(1)	(2)	(3)
Age	−0.0049	−0.0057*	−0.0046
	(0.0030)	(0.0033)	(0.0032)
Age^2 (1,000)	0.0863**	0.0974**	0.0823**
	(0.0359)	(0.0396)	(0.0390)
Married	0.0438**	0.0447**	0.0434**
	(0.0218)	(0.0214)	(0.0219)
Foreigner	0.0396	0.0394	0.0397
	(0.0418)	(0.0430)	(0.0416)
Female	−0.0016	0.0000	−0.0022
	(0.0081)	(0.0087)	(0.0085)
Medium Education (ISCED 3-4)	−0.0262	−0.0240	−0.0270
	(0.0199)	(0.0213)	(0.0207)
High Education (ISCED 5-6)	−0.1371***	−0.1312***	−0.1393***
	(0.0471)	(0.0508)	(0.0491)
Year 2003	−0.2673**	−0.2560*	−0.2715**
	(0.1319)	(0.1329)	(0.1291)
Local LTU Rate	0.1973**	0.1914*	0.1995**
	(0.0975)	(0.0981)	(0.0959)
Population (1,000)	−0.0140	−0.0107	−0.0152
	(0.0374)	(0.0378)	(0.0363)
Share of Highly Educated	−0.0112	−0.0159	−0.0095
	(0.0193)	(0.0213)	(0.0211)
Share of Foreigners	0.0182	0.0203	0.0174
	(0.0117)	(0.0127)	(0.0134)
$\bar{\omega}_{jt}$		−0.1554	0.0566
		(0.1141)	(0.2044)
Constant	−0.0581	−0.0589	−0.0578
	(0.1385)	(0.1401)	(0.1380)
R^2	0.025	0.026	0.026

Note: 21,237 observations; Standard errors in parentheses.
Standard errors are robust and clustered on cells (198 cells)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: First Stage Statistics for IV Models in Table 13

	Endogenous Variable				
	LTU Rate	Population	Education Share	Foreigner Share	$\bar{\omega}_{jt}$
IV Model 1					
Shea-Partial R^2	0.0097	0.0059	0.0086	0.019	
F-1^{st} Stage	11.274	15.316	13.798	23.521	
IV Model 2					
Shea-Partial R^2	0.0099	0.0057	0.0073	0.0194	
F-1^{st} Stage	12.711	15.169	13.307	24.266	
IV Model 3					
Shea-Partial R^2	0.0098	0.0059	0.0078	0.0198	0.0713
F-1^{st} Stage	10.418	12.265	11.392	26.64	165.206

Table 15: Significance Tests

Model	Test Statistic	p-Value
OLS 1	F(1,3031) = 12.722	0.9998
OLS 2	F(1,3031) = 8.894	0.9986
OLS 3	F(1,3031) = 8.19	0.9979
IV 1	F(1,193) = 3.503	0.9686
IV 2	F(1,193) = 2.591	0.9454
IV 3	F(1,193) = 4.316	0.9805

Note: Results from one-sided t-test with $H_0 : \theta > 0.0081$
Coefficients from Tables 2 and 3.