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In Good Company – Neighborhood Quality and Female Employment

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In Good Company – Neighborhood Quality and Female Employment

Abstract

Using a uniquely assembled panel dataset, we estimate the impact of neighborhood and peer effects on female labor supply. Nonrandom sorting and unobserved heterogeneity at the individual and neighborhood levels make recovering these impact parameters more complicated in the absence of (quasi-)experimental variation in neighborhood attributes. Our estimation strategy rests on using a hedonic pricing model to control for neighborhood-level unobserved heterogeneity and using a fixed-effects approach to account for the correlation induced by individual time-invariant unobservables. The results suggest that women's participation behavior is significantly associated with peer and neighborhood attributes. The extensive margin is driven by the average female employment rate; the intensive margin is driven by the average share of full-time employed females in the neighborhood. These relationships are stronger in the subsample of mothers. However, these statistically significant associations do not survive when we control for individual time-invariant unobservable heterogeneity.

JEL Classification: R23, J13, J22

Keywords: Neighborhood effects; female labor supply; social interactions; peer effects

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1 Introduction

While the influence of individual and household characteristics as well as the accessibility of childcare facilitites on the labor-market integration of women has been extensively analyzed (for an early survey, see Killingsworth and Heckman [1986]), the role of the environment—or, more generally, the social milieu—in this nexus has historically received less attention (Brock and Durlauf [2001b] provide a modern survey). Yet the individual decision of women, especially mothers, to supply labor is most likely influenced by neighborhood characteristics, including the extent of information networks and the state of labor demand, as well as the prevailing social mores on gender roles. Neighborhood and social-interaction effects on labor-market outcomes have thus received pronounced attention in the more recent economic literature (e.g., Bayer, Ross and Topa [2008], Buchinsky, Gotlibovski and Lifshitz [2014], Damm [2014], Dujardin and Goffette-Nagot [2010], and Maurin and Moschion [2009]), as they can possibly explain variations in individual outcomes that cannot be fully accounted for by individual and household characteristics [Graham 2008].

The interdependence between neighbors' behavior and individual behavior may create social-multiplier effects which allow for behavioral spillovers between individuals to occur [Brock and Durlauf 2001b; Manski 1993; Topa 2001]. In the presence of neighborhood and peer effects, therefore, estimates of the impact of labor-market policies may be inconsistent. Neighborhood effects may enhance the effectiveness of interventions since the effects can propagate to initially nontreated individuals via social interactions with treated individuals within the same neighborhood. For example, training programs that aim to decrease unemployment spells may impact on nonparticipants as information (say, in the form of knowledge about job vacancies or skill upgrading) spreads across the social network [Bayer, Ross and Topa 2008; Calvó-Armengol and Jackson 2004; Topa 2001]. It is also quite possible that mothers who have been deterred from entering the formal labor market by the potential social stigma attached to working mothers may be encouraged to seek employment once they recognize that members of their peer group are increasingly employed, especially given a preference for conformity (e.g., Akerlof [1997]).

The existence of these spillover effects makes the structure of the network itself a potential target for policy instruments. It raises the possibility that deliberately altering neighborhood composition can improve labor-market outcomes. For instance, the Moving to Opportunity for Fair Housing (MTO) program of the US Department of Housing and Urban Development was a randomized experiment where vouchers were distributed to low-income families to encourage them to move to better neighborhoods [Katz, Kling and Liebman 2001; Kling, Liebman and Katz 2007]. Estimating the impact of such a program is relatively easy, since the attributes of the neighborhood were experimentally manipulated, and are therefore exogenous to the experimenters' outcomes of interest. However, these estimates apply to a select subpopulation and do not inform on the impact of neighborhood and peer characteristics for those who self-select into particular neighborhoods.

Without exogenous variation in neighborhood characteristics, however, it is difficult to obtain consistent estimates of their impacts on individual labor-market outcomes because of the sorting behavior of individuals across neighborhoods [Angrist 2014; van Ham et al. 2012].[1] Suppose location choice is a nonrandom function of unobserved regional amenities [Galster 2008; Hedman, van Ham and Manley 2011]. One can expect that high-ability individuals—an attribute that is also generally unobservable—will sort themselves into neighborhoods with excellent amenities, thereby generating a correlation between individual characteristics and unobserved neighborhood attributes [Moretti 2013]. Even with the inclusion of neighborhood fixed effects in the model, the problem persists because individual unobservables will still generate a correlation with the group-level variables. Therefore, in a model with both individual- and group-level unobserved heterogeneity, and with nonrandom sorting, estimating neighborhood effects is somewhat more complex than a simple comparison of mean outcomes.

This paper is concerned with the labor-market integration of women in general and mothers in particular. Specifically, we estimate the effect of neighborhood characteristics, including peer attributes, on female labor supply at both the extensive (i.e., employment status) and intensive margins (i.e., working full-time conditional on employment) in the presence of nonrandom sorting and unobserved heterogeneity.Using a unique collection of geographically matched datasets that allow us to control for both neighborhood and individual heterogeneity, we provide estimates of neighborhood and peer effects on women's labor supply, with a special focus on mothers—a subgroup that traditionally exhibits less attachment to the labor

[1] Examples of studies that exploit random assignment are Katz, Kling and Liebman [2001], who examined neighborhood effects, and Sacerdote [2006], who estimated peer effects.

market.

In our analysis, we principally use the German Socio-Economic Panel (SOEP), which we complement with administrative and regionally aggregated labor-market statistics based on the Integrated Employment Biographies (IEB), information on daycare establishments, as well as data on house prices obtained from an internet platform for real estate. To take into account the bias induced by nonrandom sorting, we adopt a control-function approach proposed by Bayer and Ross [2009] which leverages a generated proxy for unobserved neighborhood characteristics. We eliminate the remaining individual-level heterogeneity by estimating the model via fixed effects.

Our paper makes the following contributions to the literature on the determinants of female labor supply. First, we present estimates of the impact of both "exogenous" neighborhood characteristics, such as the share of highly-educated individuals and the share of foreigners, and the "endogenous" neighborhood attribute (i.e., the share of employed women), which we use interchangeably with the peer effect.[2] These estimates are purged of the impact of neighborhood selection and unobserved heterogeneity. Second, neighborhood and peer effects are provided for both the extensive and intensive margins of female labor supply. Third, we examine whether the magnitude of neighborhood and peer effects varies over the degree of labor-market attachment by differentiating between females in general and mothers in particular. Fourth, we generate evidence of neighborhood and peer effects based on observed equilibrium outcomes, thereby providing more generalizable statements under certain conditions. In contrast, other estimates of neighborhood effects have come from (quasi-)experimental data, and this limits their application to select subpopulations.

Three further contributions are in relation to the empirical application of the strategy which Bayer and Ross [2009] first apply. First, our measure of unobserved neighborhood attributes is based on extremely detailed proprietary data that allow us to estimate a richer hedonic pricing model. Second, we rely on more identifying information to estimate the model because our data encompass more than just one metropolitan housing market. Third, since our analysis is based on panel data, we are able to rely on an identification strategy that allows us to control for time-invariant fixed effects at the individual level. This is where we depart from Bayer and Ross [2009], who use a cell-based instrumental-variable strategy instead.

[2] The distinction between exogenous and endogenous effects are due to Manski [1993].

The empirical results can be summarized as follows. Regarding the extensive labor supply, the benchmark results suggest that women's individual employment decision is significantly correlated with the neighborhood's female employment rate. This holds true for both females in general and mothers in particular. The average share of full-time employed women in the neighborhood is positively associated with the individual intensive labor supply (i.e., working full-time, conditional on employment) of all women in the sample and the subsample of mothers. However, when we use the within estimator to capture individual time-invariant unobservable heterogeneity, we find no significant effect of neighborhood characteristics on the extensive and intensive labor supplies for both women in general and mothers in particular. The results show that neighborhood characteristics, both observed and unobserved, do not significantly affect female labor supply, although this conclusion is contingent on having sufficient within variation in the variables used in the analysis. The conclusions are robust to a number of sensitivity checks described below.

2 Neighborhood Effects and Female Labor Supply

In this section, we discuss the link between labor-market outcomes and neighborhood attributes. In particular, we mention several causal mechanisms through which residential choice and neighborhood characteristics can influence labor-market participation. Difficulties in estimating the neighborhood effects in the absence of exogenous variation in neighborhood characteristics are highlighted. Finally, we refer to previous studies that characterize the participation decision of females in the labor market.

2.1 Link Between Labor-Market Outcomes and Neighborhood Attributes

The literature on the impact of neighborhood attributes on individual behavior is growing, drawing inputs from allied social sciences (Durlauf [2004] provides a survey). The broad range of outcomes that have been covered include, among others, educational attainment [Garner and Raudenbush 1991], crime and delinquency [Kling, Ludwig and Katz 2005], and health status [Ellen, Mijanovich and Dillman 2001; Votruba and Kling 2008]. In Labor Economics, empirical studies mainly focus on how neighbors influence individual employment probabilities [Bauer, Fertig and Vorell 2011; Ioannides and Loury 2004] and welfare receipt [Kling, Liebman and Katz 2007]. Studies specifically addressing neighborhood effects on womens' individual labor supply remain scarce, but a few notable examples are available [van Ham and Büchel 2006; Johnson 2014; Maurin and Moschion 2009].

Manski [1993] provides the conventional organizing framework, where there are three neighborhood effects to consider. First, an individual's choice may be influenced by the choice of her peers—the "endogenous social effect," which is also often called the "peer effect or social spillover" [Angrist 2014, p. 104]. Second, her choice may also be affected by the characteristics of the neighborhood, which could be aggregations of her peers' characteristics—the "contextual" or "exogenous social effect." Finally, the "correlated effect" refers to the fact that individuals who face the same social milieu may act similarly because they are subjected to the same environment or they share the same unobserved characteristics.

Location choice can impact labor-market outcomes since a particular point in space is associated with a variety of factors that affect one's performance in the labor market. For instance, the proximity to jobs is, by definition, a function of spatial distance. If one lives in a poor inner-city neighborhood with limited access to efficient public transporation while jobs have migrated to suburban areas, the spatial accessibility of employment is limited. Search costs would be higher, and wages would necessarily have to be higher to compensate for increased commuting times, leading to barriers to employment for low-skilled workers whose marginal productivities are lower than the combined wage and associated costs [Ross and Zenou 2008; Weinberg, Reagan and Yankow 2004]. Therefore, even in the absence of information spillovers within a network, nonrandom sorting will result in a correlation in labor-market outcomes for people living in the same neighborhood [Topa 2001].

Employers may also use residential choice to statistically discriminate among potential employees when there are information asymmetries [Arnott 1998; Rogers 1997]. For instance, in the absence of verifiable information concerning a person's labor productivity, an employer may use information on the potential employees' residence to infer the latter's abilities. One might surmise that the inability of a person to find residence in a neighborhood with good amenities is an indication of this person's general lack of motivation. This is essentially the idea behind the spatial-mismatch hypothesis, which posits that the likelihood of employment varies with respect to residential choice [Kain 1968].

Montgomery [1991] models employers as relying on high-ability workers and their job referrals to solve the adverse-selection problem that arises out of the information asymmetry concerning a potential employee's productivity. As noted by Damm [2014], such a process reduces the costs associated with job matching, such as search and screening. This employment spillover can happen when there are social interactions—that is, when the employed individual relays the information to either the employer or the potential employee (in the form of the announcement of a job vacancy), as modeled, for example, by Calvó-Armengol and Jackson [2004]. These "non-market externalities" are assumed to occur "*locally*, with a set of neighbors defined by an economic or social distance metric", generating a natural correlation in outcomes within groups [Topa 2001, p. 261, emphasis in the original].

In addition to these contextual mechanisms, the individual's decision to supply labor may also be affected by the behavior of other members of her reference group (i.e., peers).[3] As Akerlof [1997] demonstrates, there could be utility derived from conforming with the behavior of one's peers. This might apply more to mothers, who may perhaps face some social stigma by choosing to work instead of staying at home to take care of her children. An individual may also benefit from the information supplied by members of her social network [Calvó-Armengol and Jackson 2004]. Employed women, for example, may have immediate access to posted job vacancies or insider knowledge on what is required for a particular position, and she may share this with unemployed women in her neighborhood. Topa [2001] shows that individual employment status not only depends on individual characteristics but also on the characteristics of neighbors. The estimates indicate large spillovers for areas with younger, less educated people, with lower median income, and lower labor-force participation, indicating that social effects exhibit some heterogeneity.[4]

2.2 Identification of Neighborhood Effects

It is likely that endogenous, exogenous, and correlated effects, along with individual and household attributes, jointly determine labor-market outcomes, particularly employment. First, an endogenous social effect may manifest itself by changing social norms about gender roles or

[3] Woittiez and Kapteyn [1998] provide evidence for the choice of the reference group of an individual.

[4] That peer effects may be heterogeneous across subsamples have also been empirically demonstrated in Lavy, Silva and Weinhardt [2012].

perhaps because employed individuals simply have more information about the labor market, and they may share this with others in their group (see, for instance, Calvó-Armengol and Jackson [2004]). Second, employment prospects may be influenced by the aggregate characteristics of her neighbors. For instance, residence in a depressed area or an immigrant enclave may be interpreted by employers as a negative signal. On this issue, one can explore the literature on the spatial-mismatch hypothesis (e.g., Arnott [1998] and Rogers [1997]) and spatial "redlining" (e.g., Zenou and Boccard [2000]). Third, nonrandom sorting, as discussed above, can easily result in a situation where common shocks can affect people living in the same neighborhood. An example is the closure of a military base, which is usually the main employer, in a small town (for a survey, see Droff and Paloyo [2014]).

As such, Manski [1993] points out that, in a particular class of models ("linear-in-means" models), separately identifying these effects is not straightforward. One would need either a source of exogenous variation in neighborhood and peer attributes, which is the strategy of Maurin and Moschion [2009], or to control directly for various types of heterogeneity, as in Weinberg, Reagan and Yankow [2004]. One may also assume that the exogenous effect is zero to enable the identification of the endogenous effect, which is the strategy suggested in Graham and Hahn [2005].[5]

Along the lines of using exogenous variation, there are a number of studies that use quasi-experimental changes in neighbors and peers, such as Damm [2014], Duflo and Saez [2002], Katz, Kling and Liebman [2001], Sacerdote [2006], and Zimmermann [2003].[6] Estimates of neighborhood or peer effects in these studies—although clearly internally valid—technically only apply to those who were exposed to the exogenous variation, and they may not necessarily be representative for the population [Bayer and Ross 2009; Weinberg, Reagan and Yankow 2004]. In the study of the MTO program by Katz, Kling and Liebman [2001], for instance, vouchers for moving into better neighborhoods were given to disadvantaged families. While there is a natural public concern for improving the economic outcomes of, say, the poor and unemployed, the estimated impacts for the movers will be difficult to translate for someone

[5]When one departs from linear-in-means models, more opportunities for identification exist [Brock and Durlauf 2001a,b]. See also Galster [2008] for a synthesis.

[6]Perhaps the pioneering research using this approach is the set of studies that came out of a mobility program in Chicago. As a result of the cases *Gautreaux v. Chicago Housing Authority*, 304 F. Supp. 736 (N.D. Ill. 1969) and *Hills v. Gautreaux*, 425 U.S. 284 (1976), families living in housing projects were awarded rental housing assistance to move into the suburbs. See Popkin et al. [2000] for details.

randomly drawn from the population. Moreover, such changes in neighborhoods break the social connections established in the original social milieu. It requires time for movers to assimilate and create new social networks. This process limits the generalizability of the effects of exposure to the new neighborhood.

Other researchers have tried to estimate the impact of neighborhood attributes in a more general setting where individuals are observed in equilibrium (e.g., Bauer, Fertig and Vorell [2011], Bayer and Ross [2009], Evans, Oates and Schwab [1992], Dujardin and Goffette-Nagot [2010], Dujardin, Peeters and Thomas [2009], van der Klaauw and van Ours [2003], Weinberg, Reagan and Yankow [2004]). These types of studies, where there is no exogenous intervention, are called "studies of private actions" [Moffitt 2001, p. 66]. They have the advantage of delivering estimates for the sample as it is observed on the ground, so to speak, instead of "artifically" transplanting people to a different neighborhood. In general, these studies—including our own—have to rely on any (or a combination) of a number of elements, such as nonlinearities, exclusion restrictions, and exogeneity, for identification. As a consequence, at least one prominent economist is critical of this strand of the literature on peer effects [Angrist 2014].

Methodologically, our study is closely related to Aaronson [1998], Bayer and Ross [2009], and Weinberg, Reagan and Yankow [2004]. Bayer and Ross [2009] introduce the control-function approach that we use to generate a proxy variable to account for unobserved neighborhood characteristics that determine residential choice. The remaining papers emphasize accounting for the time-invariant unobserved heterogeneity at the individual level by estimating fixed-effects models. In all cases, the authors note that ignoring the nonrandom sorting resulting from unobservable heterogeneity leads to an unreliable estimate of the impact of neighborhood attributes.

2.3 Female Labor Supply

Women exhibit peculiarities with respect to participating in the labor market which may interact meaningfully with neighborhood effects. For example, partnered women and women with children are less attached to the formal labor market because typical household specialization privileges their domestic or nonmarket work over their market work. As such, they may not be as responsive as men to neighborhood attributes that influence labor-market participation. In fact, even their spatial mobility is comparatively more limited [Weinberg, Reagan and Yankow 2004], and one can show that more women work closer to home (possibly because they take on a larger share of domestic parental responsibilities).[7] Using the subsample of women who live in Western Germany and are willing to work available in the German Socio-Economic Panel (SOEP), van Ham and Büchel [2006] find that women living in an area with a high unemployment rate are discouraged from entering the labor market.

There are also differences between men and women when it comes to job-search behavior. In Hanson and Pratt [1991] and Hanson, Kominiak and Carlin [1997], the location and occupational choices of women are significantly associated with their labor-market participation. Information channels that determine job matches are shown to be different for men and women and, specifically, for women in female-dominated occupations as opposed to women in male-dominated occupations. For instance, local or community-based contacts are more important for women. More than wage considerations, it also seems that women in female-dominated occupations value the spatial proximity of the place of work to the home and the suitability of the working hours. This is in line with Calvó-Armengol and Jackson [2004], Koning, van den Berg and Ridder [1997], and Topa [2001], who demonstrate that individuals transmit information on vacancies to each other.

Stoloff, Glanville and Bienenstock [1999] suggest that women who have diverse and extensive networks are more likely to be working for pay than women whose networks are not as diverse. Women, in contrast to men, also need social support because of their childcare responsibilities, as their findings on the effects of living with parents for a single mother suggest. Having children—especially young children—is a constraint on labor-force participation for all women. Stoloff, Glanville and Bienenstock [1999], however, neither addressed any of the endogeneity concerns that arise out of unobserved individual and/or neighborhood heterogeneity nor made mention of the difficulty of identifying peer or network effects without exogeneous variation in the explanatory variables of interest.

More recently, Johnson [2014] directly explores the causal relationship between house prices

[7] See, for example, Madden [1981]. In our sample of individuals aged 25-60, women's place of work is, on average, about 9.09 km (with a standard deviation of 24.95 km) away from home, while mothers' place of work is even closer (8.17 km with an s.d. of 30.09 km). The corresponding figure for men, in contrast, is 16.46 km with an s.d. of 54.84 km.

and female labor supply. The direction of causality can run both ways. First, rising house prices may induce more female participation in the labor market, since a dual-earner household is more likely to afford housing. Second, increasing household income can result in increasing demand for housing, which may drive up prices, especially in metropolitan areas with a relatively stable supply of units. The results do not rule out the possibility that the second channel—from participation to house prices—may exist, but there is little evidence to support the idea that house prices affect the labor-market-participation decision of women.

Apart from the current manuscript, the only other study dedicated to analyzing female labor supply which attempts to recover a credible estimate of peer effects was conducted by Maurin and Moschion [2009]. The authors use an instrumental-variable strategy with data from the French Labor Force Survey to estimate the impact of the neighbors' labor-market participation on a mother's own participation. Their estimates of the endogenous effect is around 0.6 percentage points (i.e., a 1-percentage point increase in the share of employed neighbors generates a 0.6-percentage point increase in the probability of a mother's labor-market participation; see Table 6 of their paper). In our discussion of our estimation results, we provide explanations as to why our exercise does not lead to the same conclusions.

3 Empirical Strategy

In this section, we set up the estimation problem when we allow for the possibility that unobserved heterogeneity enters the outcome equation from two sources, the individual and the neighborhood. These unobservables necessitate a more sophisticated estimation strategy than ordinary least squares to recover consistent estimates of the impact of neighborhood attributes on female labor-supply decisions. We then discuss the control-function approach described in Bayer and Ross [2009] which allows us to proxy for unobserved neighborhood characteristics. Finally, we briefly introduce the fixed-effects approach, which allows us to take into account individual time-invariant unobservable heterogeneity.

3.1 Double Heterogeneity and Nonrandom Sorting

Our empirical analysis of neighborhood effects on female labor supply begins with the conventional linear-in-means model [Brock and Durlauf 2001b; Manski 1993]. Following Bayer and Ross [2009], we augment it with two sources of unobserved heterogeneity:

$$Y_{ijt} = \boldsymbol{\beta}'\mathbf{X}_{ijt} + \boldsymbol{\gamma}'\mathbf{N}_{jt} + \theta L_{jt} + \eta_i + \lambda_{jt} + \boldsymbol{\tau}_t + \epsilon_{ijt}, \tag{1}$$

where Y_{ijt} is the outcome variable indicating the labor supply of individual i living in neighborhood j at time t. In our analysis, we differentiate between the extensive and intensive margin of labor supply by estimating separate models. The vector $\mathbf{X}_{ijt}$ represents observable individual and household characteristics, $\mathbf{N}_{jt}$ is a vector of observable neighborhood characteristics, and L_{jt} is, first, the female employment rate in the model for the extensive margin and, second, the share of full-time employed women in the model for the intensive margin. Time-invariant individual and time-varying neighborhood unobserved heterogeneity are represented by η_i and λ_{jt}, respectively, while $\boldsymbol{\tau}_t$ represents a vector of period fixed effects. The idiosyncratic error is ϵ_{ijt}.

Cast in this way, we make it explicit that a woman's decision to supply labor is a function of her own observed and unobserved attributes ($\mathbf{X}_{ijt}$ and η_i), the observed and unobserved attributes of her group and neighborhood ($\mathbf{N}_{jt}$ and λ_{jt}), and the labor-supply decisions of the other members of her group (L_{jt}). The variable L_{jt}, the vector $\mathbf{N}_{jt}$, and the heterogeneity represented by λ_{jt} constitute the totality of neighborhood attributes. In Manski's [1993] terminology, the coefficient vector $\boldsymbol{\gamma}$ captures the impact of exogenous neighborhood and social characteristics while θ represents the endogenous social effect of the neighborhood's female labor supply on the individual decision to supply labor.

Under a regime of nonrandom sorting, least-squares estimation of the parameters in Equation (1) will be biased and inconsistent. This is because location choice generates a correlation between λ_{jt} and the individual attributes $\mathbf{X}_{ijt}$ and η_i. In addition, we can also expect a nonzero correlation between the unobserved individual attribute η_i and the observed neighborhood attributes L_{jt} and $\mathbf{N}_{jt}$. This may arise because a concentration of high-ability women, as measured by η_i, can contribute to better labor-market outcomes at the neighborhood level as well as to other neighborhood attributes, such as the number of daycare centers. This kind of "self-selected migration" is documented elsewhere (e.g., Carneiro, Meghir and Parey [2002], Dahl [2002] and Solon [1999]). At its core, the setup is essentially a selection model with multiple choices (i.e., many residential areas), and to consistently estimate the impact of each neighborhood in a nonexperimental setting would require as many instrumental variables as there are neighborhoods, which is rarely possible [Dahl 2002].[8]

To properly recover the neighborhood effects γ and θ, we adopt a two-step procedure. First, we proxy for the unobservable neighborhood attribute λ_{jt} with a control function by exploiting a robust result from vertical sorting models.[9] Second, we use a fixed-effects strategy to address the remaining correlation induced by the unobservable individual attribute η_i. The idea that motivates the first step is that the unexplained portion of housing prices can serve as a proxy for unobserved neighborhood characteristics that may serve as push or pull factors in residential location choice. Once the endogeneity induced by λ_{jt} is accounted for, we can proceed to deal with the endogeneity arising out of the presence of η_i. This can be addressed by including individual-level fixed effects. Any remaining correlation in the residuals generated by observations being in the same neighborhood is accounted for by estimating standard errors that are robust to clustering at the postcode level.

3.2 Control Function and Hedonic Pricing

The first part of the estimation approach is anchored on a key insight established in locational equilibrium models [Epple and Platt 1998; Epple and Sieg 1999]. Housing prices can serve as an index of neighborhood quality—both observed and unobserved—precisely because individuals sort across different locations. More generally, the model applies to situations where group membership is priced. Conditional on an individual's characteristics, a person deciding on where to reside faces a tradeoff between neighborhood quality and the price of access.[10] Epple and Platt [1998] show that, as neighborhood quality increases, average house prices will also increase. This monotonic relationship therefore raises the possibility that a function of price can serve as a proxy (i.e., a control function) for neighborhood characteristics.

To generate a proxy variable for the unobservable neighborhood attributes, we first esti-

[8] See Geweke, Gowrisankaran and Town [2003] for an exception.

[9] This strategy was also used by Bauer, Fertig and Vorell [2011] to evaluate the impact of neighborhood unemployment on individual employment prospects. We refer the interested reader to Bayer and Ross [2009] for a more detailed treatment.

[10] Dahl [2002] has a similar framework. He generalizes Roy's [1951] model of occupational choice to a multi-location residential-choice model.

mate the following hedonic housing price function:

$$\log\left(P_{mjt}\right) = \boldsymbol{\delta}'\mathbf{H}_{mjt} + \boldsymbol{\zeta}'\mathbf{N}_{jt} + \phi L_{jt} + \boldsymbol{\tau}_t + \omega_{mjt}, \tag{2}$$

where $\log\left(P_{mjt}\right)$ 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 other variables are as previously defined, with $\boldsymbol{\delta}$ and $\boldsymbol{\zeta}$ representing vectors of parameters to be estimated. The error term ω_{mjt} captures unobservable characteristics affecting house prices.

The neighborhood averages of the residuals after estimating Equation (2) via least squares can be construed as unobservable neighborhood amenities which determine individual residential choice. This follows directly from the equilibrium result derived in Epple and Platt [1998] and Epple and Sieg [1999]—that is, higher prices (beyond those predicted by the observable housing attributes and neighborhood characteristics) correspond to better unobserved neighborhood amenities. The unit-specific residuals,

$$O_{mjt} \equiv \log\left(P_{mjt}\right) - \widehat{\log\left(P_{mjt}\right)},$$

where $\widehat{\log\left(P_{mjt}\right)}$ represents the predicted values, are averaged over each postcode per unit of time (in our case, per year) to obtain $\overline{O}_{jt} = (1/M)\sum_{m=1}^{M} O_{mjt}$, which is then included in Equation (1) as a proxy for λ_{jt}. Note that these unobservables are allowed to vary over time. At this point, the linear-in-means model is represented by the following equation:

$$Y_{ijt} = \boldsymbol{\beta}'\mathbf{X}_{ijt} + \boldsymbol{\gamma}'\mathbf{N}_{jt} + \theta L_{jt} + \kappa\overline{O}_{jt} + \eta_i + \boldsymbol{\tau}_t + \epsilon_{ijt}, \tag{3}$$

where our interest remains on the estimates of γ and θ.

3.3 Individual-Level Fixed Effects

While the model represented by Equation (3) will enable us to control for time-varying unobservable neighborhood attributes that determine sorting, the presence of unobservable individual heterogeneity, η_i, will still generate a nonzero correlation between ϵ_{ijt} and $\mathbf{N}_{jt}$, L_{jt}, and even $\overline{O}_{jt}$, thereby making the least-squares estimator inconsistent. For example, high-ability females are more likely going to reside in areas with better amenities, observable or otherwise.

To address the endogeneity of these neighborhood attributes in the individual-level outcome equation, we use the fixed-effects estimator, which is well known in the literature.[11]

4 Data Description

To estimate the impact of neighborhood attributes on extensive and intensive margins of female labor supply, we construct a unique dataset by combining information on individual and neighborhood characteristics from a variety of sources. It is crucial to note at this point that all the datasets that we employ for this study are geo-referenced and can thus be merged with each other by using the spatial identifiers. In this section, we describe these constituent datasets and the information we extract for the analysis, and we provide descriptive statistics that motivate the following econometric analysis.

4.1 Datasets

The empirical analysis is based on a unique dataset which combines longitudinal household data from the German Socio-Economic Panel (SOEP)[12] and administrative labor-market statistics from the Integrated Employment Biographies (IEB) made available by the Research Data Center of the Federal Employment Agency at the Institute for Employment Research.[13] The dataset is augmented with information on the availability of childcare facilities provided by the Statistical Offices of the Federal States and the Federal Statistical Office. Finally, we also use data on house prices and house characteristics provided by the largest online real-estate platform in Germany, *ImmobilienScout24*.

The SOEP, which started in 1984, is a representative household panel study in which annual personal interviews are conducted with all adult household members [Wagner, Frick and Schupp 2007]. The study is based at the German Institute for Economic Research (DIW) in Berlin. About 11,000 households and over 20,000 persons are surveyed annually. These in-

[11] See Wooldridge [2013] for a textbook treatment.

[12] 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.

[13] The combined "German Neighborhood SOEP" is a joint project of the Research Data Center (FDZ) at the Institute for Employment Research (IAB), the Deutsches Institut für Wirtschaftsforschung (DIW), and the Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI) with financial support from the Leibniz Gemeinschaft.

dividuals provide information on socioeconomic, demographic, geographic, and other characteristics, such as household composition and family background. We exclude males in our analysis. Female labor supply (the outcome variable), Y_{ijt}, is defined in two ways based on information from the SOEP. First, it is a binary indicator for being employed; second, it is a binary indicator for being full-time employed for the subsample of employed women. The first and second definitions capture the extensive and intensive margins, respectively, of female labor supply.

A number of individual and household characteristics are also drawn from the SOEP. These correspond to the vector $\mathbf{X}_{ijt}$, which contains variables that are likely to influence women's individual labor supply. These are age in years, the number of children (aged 0–3, 3–6, and 6–14) in the household, and the net income of the partner living in the household in the previous month. Variables indicating civil status, German citizenship, educational attainment, the labor-market status of the partner, and whether the partner is living in the household are also included. In measuring the individual's educational attainment, we create a categorical variable indicating low, medium, and high attainment based on bands of the International Standard Classification of Education (ISCED). Specifically, ISCED 0–2 (no, basic, and lower-secondary schooling) refers to low attainment, ISCED 3–4 (upper secondary and any post-secondary schooling) refers to medium attainment, and ISCED 5–6 (tertiary and higher education) refers to high attainment. The sample is restricted to women aged between 25 and 60 years who are either the household head or the partner of the household head. The exclusion based on age reduces the likelihood that we include in the sample females who have not yet finished their educational career and those who are contemplating retirement. In other words, our focus is on the period of the lifecycle that is post-schooling and pre-retirement.

The labor-market statistics, which are available for the period 2004–2010, are drawn from the IEB, which are process-generated data based on administrative employment and unemployment records collected by the German Federal Employment Agency. Individuals are included in the dataset if they are either employed in a position subject to social security contributions or registered as unemployed. The biographies are used to construct postcode-level aggregated information on the share of highly educated people (defined as those with a tertiary education degree, which is used to capture the stock of human capital in the neighborhood), and the share of foreigners. These variables constitute the vector $\mathbf{N}_{jt}$ in our model. The employment rate of women aged 25–60 as well as the the share of full-time employed women aged 25–60 are also calculated from the IEB, and this corresponds to the extensive and intensive margins of the neighborhood's female labor supply, L_{jt}, in the model, representing the influence of peers in individual decision-making.

Since the availability of childcare facilities in the neighborhood is a crucial determinant of the extensive and intensive margins of labor supply of women with small children [Ribar 1992], we additionally use data on daycare establishments provided by the Statistical Offices of the Federal States and the Federal Statistical Office. These county-level data are available for the years 2006–2012, and allow us to construct further neighborhood control variables that indicate the proportion of children (aged 0–2 and 3–6) enrolled in daycare establishments. These variables also enter the vector $\mathbf{N}_{jt}$.

To estimate our hedonic pricing model in Equation (2), we need information on house prices and corresponding house characteristics. This is obtained from *ImmobilienScout24*, which provided us with all recorded offers for the years 2007–2013.[14] According to its website, *ImmobilienScout24* receives about 1.5 million different properties either for rent or for sale per month. It has more than 2 billion page impressions per month, with over 100,000 property sellers. Of those using the Internet to search the market for real estate, about 88.5 percent use this portal. The platform covers about 35.7 percent of all rental contract conclusions in Germany.[15]

The estimation sample for the hedonic pricing model consists only of houses for sale. The variables that we use to explain the selling price of the housing unit are the age of the house in years, its size, and categorical variables indicating its type and state. Regarding the type, housing units are differentiated between (1) single detached, (2) multi-storey, (3) farmhouse, bungalow, villa, special, (4) terrace, terrace-middle, (5) terrace-end, (6) semi-detached, and (7) other. The state or condition of the unit falls into one of four categories: (1) new, like new, or just-renovated; (2) completely renovated or renovated (but not necessarily the first occupant post-renovation); (3) modernized or well-kept; and (4) in need of renovation, needs a discussion, or no description. These variables constitute the vector $\mathbf{H}_{mjt}$ and, together with $\mathbf{N}_{jt}$ and L_{jt}, are used as covariates in Equation (2) to predict house prices.

[14] For a documentation of this dataset, see an de Meulen, Micheli and Schaffner [2014].

[15] This information is available on the website of *ImmobilienScout24*. URL: <`https://www.immobilienscout24.de/`>. Accessed 27 November 2014.

For the empirical analysis, the aggregated labor-market statistics as well as the residuals from the housing-price model are merged into the individual SOEP data at the level of more than 3,500 postcode areas. Furthermore, the information on the proportion of children enrolled in daycare facilities is merged at the level of more than 400 counties (NUTS 3).[16] As the housing price data are not available before 2007, the analysis focuses on the period from 2007 to 2010, when our IEB data cease. Women who moved during the analysis period were dropped from the estimation, but this only constitutes about 5 percent of the sample.[17] The resulting operational sample is an unbalanced panel with about 10,900 observations for more than 4,000 women aged 25–60.

4.2 Descriptive Statistics

Unweighted summary statistics on individual and neighborhood characteristics used in the empirical analysis are provided in Table A.1. The share of employed women aged 25–60 is 75 percent in our sample, and, among those who are employed, 52 percent work full-time. The statistics on the main neighborhood characteristics, however, reveal that the average female employment rate is about 93 percent, with 52.5 percent of them working full-time. The differences between the employment rate at the individual and neighborhood levels can be attributed to the fact that the IEB dataset does not include nonparticipants in the labor market while the SOEP is a representative household survey.

The average age of the females in our sample is about 45 years, more than 70 percent are married, and about 85 percent are German citizens. In terms of educational attainment, 14 percent are low-educated (ISCED 1–2), 57 percent are medium-educated (ISCED 3–4), while women with the highest educational qualifications (ISCED 5–6) make up about 29 percent. About 80 percent of the females in our sample live together with a partner in the same household (66 percent with an employed and 13 percent with an unemployed or inactive partner).

[16] NUTS 3 (Nomenclature of Territorial Units for Statistics 3) of Germany are districts or counties (*Kreise und kreisefreie Städte*).

[17] To the extent that reverse causality can occur—for instance, an exogenous employment shock can cause a person to change neighborhoods—the sample of movers could be exploited to test its existence. As in Weinberg, Reagan and Yankow [2004], one could show that employment is rather stable before any residential changes, which would indicate—albeit not conclusively—that reverse causality is not a cause for concern. Their results indicate that the number of hours worked in the years before moving are rather stable, although there is a slight increase after moving into better neighborhoods. Unfortunately, we do not have enough observations to meaningfully test the same hypothesis. In any case, this kind of reverse causality will only tend to inflate the estimated effects.

For those with an unemployed or inactive partner and those with no partner present in the household, the partner's income is set to zero. Based on the IEB dataset, the average share of foreigners in the neighborhood is about 9 percent, and the respective share of workers with a tertiary schooling degree is about 9.6 percent. The divergence from the corresponding individual characteristics can be attributed again to the difference in sampling design.

Summary statistics on house characteristics used in generating the residuals from Equation (2) are provided in Table A.2. The mean house size is 157 square meters. The mean age is 38 years, with the oldest building in the sample being 140 years; recently-built houses are coded with an age of zero. More than half of the houses have a cellar. In terms of the condition of the units in the sample, about 18 percent of the houses are like new or first move-in, 5 percent are renovated, and 33 percent are modernized or well-kept. The remaining 44 percent are either not renovated or unknown.[18] The housing type characterizes the stock of houses in Germany and reflects the distribution of housing types sold. Around 39 percent of the houses sold were single detached and 16 percent are semi-detached. Seventeen percent of the houses in our sample are terrace houses, with 12 percent being terrace or terrace-middle, and 5 percent being terrace-end houses. Moreover, the dataset contains about 7 percent "farmhouse, bungalow, villa or special" and about 12 percent are classified as "other."

Table 1 displays the mean of women's individual labor supply for each tertile of the neighborhood characteristics under consideration. For both women and mothers, the extensive labor supply is positively correlated with the average employment rate, the share of highly educated, and the share of small children (aged 0–3) in daycare, while it is negatively correlated with the average share of foreigners. The share of children aged between 3 and 6 in childcare appears not to be correlated with the individual decision to participate in the labor market. This, however, is the case when it comes to the decision to work either part-time or full-time. Moreover, the descriptive statistics on intensive labor supply indicate that the women's individual probability of working full-time increases with the average share of females working full-time, the share of highly educated, as well as with the share of children (0–3) in daycare. Mothers' intensive labor supply additonally tends to increase with the average share of foreigners, while there appears to be no correlation with the share of highly educated people.

[18] These conditions are self-reported either by the house owner or the realtor.

TABLE 1
INDIVIDUAL LABOR SUPPLY AND NEIGHBORHOOD CHARACTERISTICS

	Extensive labor supply		Intensive labor supply	
	Females	Mothers	Females	Mothers
Neighbors' participation decision[a]				
Low	0.70	0.64	0.48	0.24
Medium	0.74	0.67	0.51	0.26
High	0.79	0.70	0.63	0.34
Share of foreigners				
Low	0.76	0.72	0.54	0.32
Medium	0.75	0.66	0.53	0.28
High	0.71	0.64	0.55	0.25
Share of highly educated				
Low	0.71	0.65	0.51	0.27
Medium	0.73	0.67	0.54	0.28
High	0.78	0.69	0.57	0.28
Share of children (aged 0–3) in daycare				
Low	0.71	0.65	0.49	0.24
Medium	0.75	0.78	0.56	0.28
High	0.77	0.80	0.57	0.31
Share of children (aged 3–6) in daycare				
Low	0.72	0.65	0.53	0.25
Medium	0.76	0.69	0.53	0.27
High	0.74	0.66	0.67	0.31

NOTES.—[a] The participation decision of the neighbors refers to the share of women employed in the neighborhood when considering the extensive labor supply and the share of women in full-time employment when considering the intensive labor supply.
SOURCE.—Authors' calculations based on SOEP and IAB.

5 Results

In this section, we initially present the results from the hedonic pricing model, which we use to generate a proxy for time-varying unobserved neighborhood attributes. We then discuss the regression results for our models of both the extensive and intensive margins of female labor supply, with and without accounting for individual-level heterogeneity. Ultimately, the results of our preferred models suggest that—following the terminology of Manski [1993]—both endogenous and exogenous peer effects do not significantly impact females' labor supply for both intensive and extensive margins. Unobserved neighborhood attributes, as captured by our proxy variable, also do not significantly explain the participation decision.

5.1 Hedonic Pricing Model

Table A.3 displays the results obtained from estimating the hedonic house price equation (Equation (2)), which includes characteristics for the particular housing unit as well as neighborhood control variables. Column (1) uses our measure of the extensive margin while Column (2) uses our measure of the intensive margin.

Generally, the coefficient estimates conform to expectations. For instance, larger units are associated with higher prices, and those houses without cellars sell for less. It is also notable that the age of the unit has a nonlinear effect on the selling price. Relative to semi-detached houses, single detached and the category "farmhouse, bungalow, villa, special" are associated with higher prices while those units in multi-storey buildings sell for significantly less. House prices seem to have decreased over time, but there is some evidence that it has recovered right at the end of our sample period.[19]

What is perhaps curious is that a renovated house is associated with a higher selling price than a newly constructed unit, and that, for Column (1), a modernized or well-kept house is associated with a lower selling price than a unit that has not been renovated. The first may be because renovated houses could be located in prized areas in city centers while newly constructed units may be located farther into the suburbs. However, both the first and the second issue may be explained by measurement errors when assessing the state of the apartment since these are self-reported measures by either the owners or the realtor.

In terms of the neighborhood characteristics, female employment is associated with higher selling prices. In particular, one-percentage-point increases in the female employment rate and the share of women in full-time employment are associated with a 2.5-percent and a 1.5-percent increase in a unit's selling price, holding all else equal. Other neighborhood attributes that are significantly robust are the share of foreigners and the share of highly educated people, both of which are associated with higher selling prices.

These results are consistent with what has been empirically demonstrated in other settings. For instance, data from the US census in 2000 show a strong correlation between female labor-force participation and median home value in metropolitan areas (see Figure (1) in Johnson [2014]). In addition, Moretti [2013] provides evidence that changes in average rent in the period

[19] The coefficients of the vector of year indicators are not presented in the table.

1980–2000 are associated with changes in the share of college graduates over the same period (see Figure (1) of his paper).

The regional distribution of the residuals are shown in Figures 1 and 2, where the first and second correspond to the residuals which enter the extensive and intensive labor-supply regressions, respectively. In both figures, the darker areas indicate neighborhoods where the model underpredicts prices, i.e., darker dots indicating postal code areas in which individuals are willing to pay more to live than the amount attributable to observed housing and neighborhood. The lighter areas correspond to neighborhoods where the model overpredicts prices.

In general, one can observe that the model underpredicts house prices in cities, with the most prominent ones being Berlin, Hamburg, Munich, Stuttgart, and the metropolitan area of the Ruhr region. This indicates that there are strong unobservable factors in these regions that drive housing prices upward. These factors could, for example, take the form of agglomeration or network effects that are usually observed in cities and other densely populated areas. Conversely, one can also clearly see that overprediction occurs in more rural areas. In order to take into account these unobservable neighborhood characteristics, we merge the average regional residuals with the individual SOEP data and include them as a proxy for neighborhood quality in our model for both extensive and intensive labor supply. It appears as $\overline{O}_{jt}$ in Equation (3).

It should be noted that none of these estimated coefficients should be interpreted as estimates of the causal impacts of these specific housing and neighborhood characteristics. The purpose of estimating the hedonic pricing model is to predict housing prices—which the model does reasonably well as indicated by the R^2 of about 68 percent—so that we can calculate the residuals. These differences in the predicted and actual house prices are then averaged at the postcode level and are used as an index for unobserved neighborhood attributes that may explain female labor-force participation.

5.2 Extensive and Intensive Female Labor Supply

We present the estimation results for the labor-supply models in two waves. First, we present the estimation results from the linear probability models without taking into account individual-level fixed effects. Second, we present the results using the within estimator which accounts for the time-invariant unobserved heterogeneity.

5.2.1 Least Squares without Unobserved Heterogeneity

The baseline results obtained from estimating Equation (3) by OLS without controlling for η_i are displayed in Tables 2 and 3. They provide insights on how individual characteristics as well as neighborhood characteristics and neighborhood quality are correlated with the individual labor supply of women in general (Columns (1)–(3)) and mothers in particular (Columns (4)–(6)). In Columns (1) and (4), we only control for individual characteristics and the female employment rate in the corresponding neighborhood. Further characteristics at the neighborhood level are added in Columns (2) and (5) while Columns (3) and (6) additionally include $\overline{O}_{jt}$, the residual obtained from estimating the hedonic housing price function (Equation (2)) which measures the unobservable neighborhood quality.

Regarding the extensive labor supply of women and mothers (Table 2), the estimated coefficients on individual characteristics show the expected signs and are statistically significant, except the marital status of mothers. Women's employment probability shows an inverted U-shaped pattern of age, increases with the educational level, and decreases with the number of children, especially younger children. Moreover, women living together with an employed partner are more likely to be employed than women with no partner or an unemployed partner in the household. This may be due to differences in the access to job networks or a result of positive assortative mating, meaning that people with similar traits will pair up to maximize the household's production [Brien and Sheran 2003]. Partner's income is negatively correlated with the employment probability, with the effect being larger for mothers than for women, reflecting perhaps specialization as a result of intrahousehold bargaining.

The average female employment rate in the neighborhood is positively correlated with the individual employment probability. Adding further characteristics at the neighborhood level reveals that women are more likely to be employed when they live in neighborhoods with a higher share of highly educated individuals, although that is not the case when the sample is restricted to mothers. Moreover, the share of foreigners, the share of children in daycare, as well as the neighborhood-quality control variable $\overline{O}_{jt}$ are all insignificant. For women as well as mothers, the inclusion of observable neighborhood characteristics has a significant impact

TABLE 2
INDIVIDUAL EXTENSIVE FEMALE LABOR SUPPLY: OLS

	Females			Mothers		
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.0508***	0.0510***	0.0511***	0.0409**	0.0410**	0.0410**
	(0.00591)	(0.00594)	(0.00595)	(0.0172)	(0.0173)	(0.0173)
Age, squared (÷ 1000)	-0.641***	-0.644***	-0.645***	-0.503**	-0.504**	-0.504**
	(0.0693)	(0.0694)	(0.0695)	(0.221)	(0.222)	(0.222)
Married	-0.0306**	-0.0267*	-0.0271*	0.0141	0.0260	0.0260
	(0.0151)	(0.0151)	(0.0151)	(0.0276)	(0.0274)	(0.0275)
High education	0.248***	0.238***	0.238***	0.242***	0.222***	0.222***
	(0.0219)	(0.0227)	(0.0227)	(0.0342)	(0.0355)	(0.0356)
Medium education	0.148***	0.145***	0.145***	0.135***	0.130***	0.130***
	(0.0209)	(0.0211)	(0.0211)	(0.0325)	(0.0328)	(0.0328)
German citizen	0.0671***	0.0644***	0.0646***	0.0844***	0.0803***	0.0803***
	(0.0192)	(0.0193)	(0.0194)	(0.0274)	(0.0276)	(0.0276)
No. of children (aged 0–3)	-0.364***	-0.363***	-0.363***	-0.351***	-0.349***	-0.349***
	(0.0181)	(0.0181)	(0.0181)	(0.0233)	(0.0234)	(0.0234)
No. of children (aged 3–6)	-0.0914***	-0.0923***	-0.0923***	-0.0766***	-0.0795***	-0.0795***
	(0.0170)	(0.0170)	(0.0170)	(0.0206)	(0.0204)	(0.0204)
No. of children (aged 6–14)	-0.0684***	-0.0676***	-0.0676***	-0.0533***	-0.0508***	-0.0508***
	(0.00944)	(0.00942)	(0.00943)	(0.0153)	(0.0152)	(0.0152)
Partner employed	0.138***	0.140***	0.140***	0.172***	0.170***	0.170***
	(0.0221)	(0.0221)	(0.0221)	(0.0429)	(0.0433)	(0.0433)
No partner in household	0.0685***	0.0702***	0.0700***	0.0783*	0.0805*	0.0805*
	(0.0236)	(0.0236)	(0.0236)	(0.0474)	(0.0477)	(0.0477)
Partner's income (÷ 1000)	-0.0148***	-0.0154***	-0.0155***	-0.0287***	-0.0284***	-0.0284***
	(0.00454)	(0.00457)	(0.00457)	(0.00920)	(0.00917)	(0.00918)
Female employment rate	0.00730***	0.00597***	0.00594***	0.00556*	0.00617*	0.00617*
	(0.00170)	(0.00212)	(0.00212)	(0.00311)	(0.00374)	(0.00374)
Share of highly educated		0.00254**	0.00260**		0.00306	0.00306
		(0.00116)	(0.00116)		(0.00212)	(0.00214)
Share of foreigners		-0.00104	-0.00106		-0.000864	-0.000864
		(0.00111)	(0.00111)		(0.00183)	(0.00183)
Share of children (aged 0–3) in daycare		-0.000135	-0.0000970		0.00197*	0.00197*
		(0.000640)	(0.000641)		(0.00115)	(0.00114)
Share of children (aged 3–6) in daycare		0.00123	0.00120		-0.000736	-0.000733
		(0.00146)	(0.00146)		(0.00265)	(0.00263)
$\overline{O}_{jt}$			0.0185			-0.000690
			(0.0222)			(0.0393)
Constant	-1.065***	-1.069***	-1.065***	-0.798*	-0.842*	-0.842*
	(0.200)	(0.259)	(0.259)	(0.425)	(0.501)	(0.501)
Observations	10959	10959	10959	3887	3887	3887
R^2	0.155	0.157	0.157	0.170	0.174	0.174

NOTES.—The reference category for educational attainment is low education. Indicators for the observation year are included. Standard errors are robust to clustering at the postcode level and are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE.—Authors' calculations based on SOEP, *ImmobilienScout24*, and IAB.

on the estimated relationship between the average female employment rate and the individual employment probability. Notably, the proxy variable $\overline{O}_{jt}$ does not matter as much as the other observable neighborhood characteristics.

In terms of the individual intensive labor supply (Table 3), the average share of full-time employed women in the neighborhood is significantly positively correlated with the individual decision to work full-time. This is true for both women in general and mothers in particular, with the correlation being much stronger for mothers. When observable neighborhood characteristics and the proxy for unoservable neighborhood quality are added, the relationship decreases to 0.57 percent for women and 0.83 percent for mothers. Except for the average share of children in daycare, which exhibits a significantly positive correlation with the individual intensive labor supply, all coefficients of the neighborhood characteristics are insignificant. As in the case for the extensive labor supply, the change in the estimated coefficient of the neighborhood employment rate is largely driven by the observable neighborhood characteristics.

5.2.2 Fixed-Effects Models

The estimation results obtained from using a fixed-effects approach in order to take into account the unobserved time-invariant individual heterogeneity are displayed in Tables 4 and 5. Columns (1) and (4) of Table 4 refer to the baseline specifications, where only individual characteristics and the average labor supply of women in the neighborhood is included. In Table 5, the average labor supply is replaced with the share of women in full-time employment. In both tables, Columns (2)–(3) and (5)–(6) include further neighborhood characteristics. We convert the age variable into indicator variables for age brackets for the purposes of the within estimator so that the age effect can be approximated while controlling for year indicators.

With respect to the extensive labor supply of women, Table 4 shows positive effects of the regional female employment rate on the individual employment probability, which are similar in magnitude compared to the OLS results, although the coefficients are not precisely estimated. In the most preferred model (Column (3)), a one-percentage-point increase in the female employment rate in the neighborhood increases the probability of being employed by 0.71 percent, which is slightly lower than the baseline estimate which does not control for neighborhood attributes. Looking at the magnitude of the coefficients, mothers seem to respond more to the influence of their peers. In the model that includes observed neighborhood attributes and a proxy for the unobserved attributes, a one-percentage-point increase in the female employment rate is expected to lead to a 1.84-percent increase in the probability of a mother to be employed. None of the estimated coefficients are significantly associated with

TABLE 3
INDIVIDUAL INTENSIVE FEMALE LABOR SUPPLY: OLS

	Females			Mothers		
	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.0101	-0.0112	-0.0109	0.00578	0.00752	0.00754
	(0.00812)	(0.00814)	(0.00815)	(0.0256)	(0.0253)	(0.0252)
Age, squared (÷ 1000)	0.0225	0.0324	0.0289	-0.0523	-0.0678	-0.0680
	(0.0957)	(0.0958)	(0.0960)	(0.321)	(0.316)	(0.316)
Married	-0.150***	-0.150***	-0.151***	-0.0978**	-0.0906**	-0.0906**
	(0.0240)	(0.0239)	(0.0239)	(0.0426)	(0.0420)	(0.0420)
High education	0.129***	0.129***	0.129***	0.0891*	0.0828	0.0827
	(0.0339)	(0.0343)	(0.0342)	(0.0519)	(0.0524)	(0.0526)
Medium education	0.0183	0.0186	0.0187	-0.0120	-0.0172	-0.0172
	(0.0333)	(0.0333)	(0.0332)	(0.0488)	(0.0487)	(0.0488)
German citizen	-0.0130	-0.0161	-0.0154	-0.0882**	-0.100**	-0.100**
	(0.0277)	(0.0278)	(0.0278)	(0.0428)	(0.0425)	(0.0426)
No. of children (aged 0–3)	-0.308***	-0.309***	-0.307***	-0.119***	-0.110***	-0.110***
	(0.0296)	(0.0298)	(0.0298)	(0.0360)	(0.0354)	(0.0354)
No. of children (aged 3–6)	-0.235***	-0.238***	-0.238***	-0.0696**	-0.0676**	-0.0676**
	(0.0226)	(0.0225)	(0.0225)	(0.0295)	(0.0297)	(0.0298)
No. of children (aged 6–14)	-0.184***	-0.183***	-0.184***	-0.0453*	-0.0407*	-0.0406*
	(0.0154)	(0.0154)	(0.0154)	(0.0246)	(0.0243)	(0.0243)
Partner employed	-0.0912***	-0.0934***	-0.0931***	-0.214***	-0.233***	-0.233***
	(0.0317)	(0.0316)	(0.0316)	(0.0679)	(0.0663)	(0.0663)
No partner in household	-0.0867**	-0.0835**	-0.0844**	-0.226***	-0.223***	-0.223***
	(0.0340)	(0.0339)	(0.0339)	(0.0771)	(0.0758)	(0.0757)
Partner's income (÷ 1000)	-0.0281***	-0.0264***	-0.0268***	-0.0503***	-0.0445***	-0.0445***
	(0.00746)	(0.00756)	(0.00759)	(0.0106)	(0.0108)	(0.0109)
Share of women in full-time employment	0.00767***	0.00567***	0.00569***	0.0114***	0.00834***	0.00834***
	(0.00138)	(0.00198)	(0.00198)	(0.00246)	(0.00306)	(0.00306)
Share of highly educated		-0.000661	-0.000491		-0.00183	-0.00184
		(0.00165)	(0.00167)		(0.00269)	(0.00269)
Share of foreigners		0.000286	0.000206		-0.00297	-0.00296
		(0.00150)	(0.00150)		(0.00259)	(0.00259)
Share of children (aged 0–3) in daycare		0.00131	0.00150		0.00360**	0.00359**
		(0.000998)	(0.00101)		(0.00174)	(0.00176)
Share of children (aged 3–6) in daycare		0.00507**	0.00503**		0.000704	0.000712
		(0.00219)	(0.00219)		(0.00369)	(0.00372)
$\overline{O}_{jt}$			0.0448			-0.00206
			(0.0307)			(0.0518)
Constant	0.806***	0.451	0.446	0.0491	0.0842	0.0834
	(0.182)	(0.277)	(0.277)	(0.524)	(0.615)	(0.614)
Observations	7095	7095	7095	2071	2071	2071
R^2	0.191	0.194	0.194	0.121	0.130	0.130

NOTES.—The reference category for educational attainment is low education. Indicators for the observation year are included. Standard errors are robust to clustering at the postcode level and are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE.—Authors' calculations based on SOEP, *ImmobilienScout24*, and IAB.

the probability of being employed at any conventional significance level.

The estimation results for the intensive labor supply (Table 5) suggest that the average share of full-time employed women in the neighborhood is not significantly correlated with the individual probability of working full-time once fixed effects at the individual level are incorporated. Similar to the fixed-effects regression for the extensive labor supply, all neighborhood characteristcs are statistically insignificant. This holds true for all three specifications as well as for women in general and mothers in particular.

TABLE 4
INDIVIDUAL EXTENSIVE FEMALE LABOR SUPPLY: FE

	Females			Mothers		
	(1)	(2)	(3)	(4)	(5)	(6)
Aged 30–35	0.00212	0.00202	0.00174	0.0142	0.0109	0.0110
	(0.0321)	(0.0321)	(0.0321)	(0.0642)	(0.0644)	(0.0644)
Aged 35–40	-0.00313	-0.00326	-0.00335	0.000503	-0.000698	-0.000315
	(0.0347)	(0.0347)	(0.0347)	(0.0764)	(0.0764)	(0.0763)
Aged 40–45	0.0111	0.0110	0.0109	-0.0217	-0.0228	-0.0218
	(0.0313)	(0.0314)	(0.0314)	(0.0820)	(0.0821)	(0.0820)
Aged 45–50	0.0356	0.0356	0.0357	-0.0469	-0.0490	-0.0480
	(0.0284)	(0.0284)	(0.0284)	(0.0915)	(0.0918)	(0.0917)
Aged 50–55	0.0309	0.0308	0.0307	-0.0726	-0.0701	-0.0701
	(0.0243)	(0.0243)	(0.0243)	(0.101)	(0.101)	(0.101)
Aged 55–60	0.0368*	0.0369*	0.0368*	-0.114	-0.115	-0.115
	(0.0191)	(0.0191)	(0.0190)	(0.108)	(0.109)	(0.109)
Married	-0.0185	-0.0182	-0.0180	-0.0208	-0.0209	-0.0212
	(0.0274)	(0.0274)	(0.0275)	(0.0565)	(0.0564)	(0.0563)
No. of children (aged 0–3)	-0.381***	-0.381***	-0.381***	-0.323***	-0.323***	-0.324***
	(0.0310)	(0.0310)	(0.0310)	(0.0357)	(0.0358)	(0.0358)
No. of children (aged 3–6)	-0.141***	-0.141***	-0.141***	-0.128***	-0.129***	-0.129***
	(0.0253)	(0.0253)	(0.0253)	(0.0296)	(0.0297)	(0.0297)
No. of children (aged 6–14)	-0.0522***	-0.0520***	-0.0522***	-0.0689***	-0.0687***	-0.0700***
	(0.0153)	(0.0153)	(0.0153)	(0.0242)	(0.0242)	(0.0241)
No partner in household	0.0584	0.0582	0.0579	0.0930	0.0943	0.0929
	(0.0392)	(0.0393)	(0.0392)	(0.0777)	(0.0778)	(0.0775)
Partner employed	0.0241	0.0242	0.0244	0.0992**	0.0985**	0.0990**
	(0.0200)	(0.0200)	(0.0200)	(0.0431)	(0.0430)	(0.0431)
Partner's income (÷ 1000)	0.00199	0.00191	0.00191	-0.0256**	-0.0250**	-0.0252**
	(0.00472)	(0.00473)	(0.00473)	(0.0106)	(0.0106)	(0.0106)
Female employment rate	0.00712	0.00639	0.00673	0.0146	0.0168	0.0177
	(0.00471)	(0.00498)	(0.00498)	(0.0111)	(0.0117)	(0.0117)
Share of highly educated		-0.00688	-0.00628		-0.00453	-0.00333
		(0.00976)	(0.00982)		(0.0211)	(0.0213)
Share of foreigners		-0.00424	-0.00399		0.0243	0.0238
		(0.0101)	(0.0101)		(0.0202)	(0.0202)
Share of children (aged 0–3) in daycare		-0.000184	-0.000148		0.00225	0.00233
		(0.00286)	(0.00285)		(0.00606)	(0.00603)
Share of children (aged 3–6) in daycare		0.000638	0.000448		0.00153	0.00106
		(0.00204)	(0.00202)		(0.00459)	(0.00453)
$\overline{O}_{jt}$			0.0243			0.0555
			(0.0230)			(0.0492)
Observations	10959	10959	10959	3887	3887	3887
Within R^2	0.0720	0.0721	0.0723	0.0796	0.0803	0.0810

NOTES.—The reference category for the age-bracket indicators is women aged 25–30. Indicators for the observation year are included. The constant is not reported. Standard errors are robust to clustering at the postcode level and are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE.—Authors' calculations based on SOEP, *ImmobilienScout24*, and IAB.

TABLE 5
INDIVIDUAL INTENSIVE FEMALE LABOR SUPPLY: FE

	Females			Mothers		
	(1)	(2)	(3)	(4)	(5)	(6)
Aged 30–35	0.0000489	0.00230	0.00243	0.116	0.122	0.126
	(0.0248)	(0.0247)	(0.0247)	(0.0967)	(0.0971)	(0.0957)
Aged 35–40	-0.0637**	-0.0620**	-0.0620**	0.0367	0.0417	0.0446
	(0.0305)	(0.0305)	(0.0304)	(0.105)	(0.105)	(0.104)
Aged 40–45	-0.0733**	-0.0728**	-0.0728**	0.0482	0.0521	0.0548
	(0.0311)	(0.0311)	(0.0311)	(0.111)	(0.111)	(0.110)
Aged 45–50	-0.0392	-0.0396	-0.0396	0.0580	0.0626	0.0669
	(0.0300)	(0.0300)	(0.0300)	(0.122)	(0.122)	(0.122)
Aged 50–55	-0.0208	-0.0209	-0.0208	0.0890	0.0855	0.0928
	(0.0275)	(0.0276)	(0.0277)	(0.142)	(0.143)	(0.143)
Aged 55–60	-0.00662	-0.00664	-0.00661	0.0670	0.0555	0.0671
	(0.0237)	(0.0238)	(0.0238)	(0.147)	(0.148)	(0.150)
Married	-0.00261	-0.00183	-0.00192	-0.0206	-0.0204	-0.0195
	(0.0259)	(0.0259)	(0.0259)	(0.0431)	(0.0424)	(0.0420)
No. of children (aged 0–3)	-0.139***	-0.140***	-0.140***	-0.0251	-0.0221	-0.0208
	(0.0409)	(0.0408)	(0.0408)	(0.0394)	(0.0394)	(0.0391)
No. of children (aged 3–6)	-0.0467	-0.0474	-0.0475	0.0285	0.0317	0.0320
	(0.0288)	(0.0288)	(0.0288)	(0.0333)	(0.0333)	(0.0331)
No. of children (aged 6–14)	-0.00760	-0.00862	-0.00861	0.0474	0.0500*	0.0511*
	(0.0182)	(0.0181)	(0.0181)	(0.0297)	(0.0298)	(0.0297)
No partner in household	0.0857*	0.0863*	0.0863*	-0.0258	-0.0155	-0.0165
	(0.0497)	(0.0496)	(0.0496)	(0.111)	(0.112)	(0.113)
Partner employed	0.00703	0.00673	0.00672	-0.101*	-0.0945	-0.0963
	(0.0225)	(0.0224)	(0.0224)	(0.0603)	(0.0601)	(0.0606)
Partner's income (÷ 1000)	-0.00638	-0.00620	-0.00621	-0.00448	-0.00491	-0.00457
	(0.00479)	(0.00478)	(0.00479)	(0.0115)	(0.0115)	(0.0114)
Share of women in full-time employment	-0.00477	-0.00492	-0.00498	-0.00379	-0.00270	-0.00387
	(0.00539)	(0.00546)	(0.00549)	(0.0118)	(0.0119)	(0.0119)
Share of highly educated		0.00262	0.00246		-0.00440	-0.00670
		(0.0109)	(0.0108)		(0.0222)	(0.0220)
Share of foreigners		0.0126	0.0125		-0.0151	-0.0152
		(0.0119)	(0.0119)		(0.0260)	(0.0259)
Share of children (aged 0–3) in daycare		-0.00451	-0.00448		-0.00802	-0.00781
		(0.00288)	(0.00288)		(0.00646)	(0.00650)
Share of children (aged 3–6) in daycare		-0.00213	-0.00212		-0.00761	-0.00740
		(0.00242)	(0.00242)		(0.00532)	(0.00527)
$\overline{O}_{jt}$			-0.00485			-0.0565
			(0.0238)			(0.0566)
Observations	7095	7095	7095	2071	2071	2071
Within R^2	0.0123	0.0137	0.0138	0.0251	0.0299	0.0311

NOTES.—The reference category for the age-bracket indicators is women aged 25–30. Indicators for the observation year are included. The constant is not reported. Standard errors are robust to clustering at the postcode level and are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE.—Authors' calculations based on SOEP, *ImmobilienScout24*, and IAB.

5.3 Subsample Analyses

We estimated identical models over a number of subsamples to demonstrate the stability of our results. These subsamples are motivated by results from previous studies which primarily demonstrate that the magnitude of peer effects is a function of labor-market attachment, whether because of, for example, ethincity [Damm 2014] or educational attainment [Topa 2001][20]. In summary, we estimated the models by educational attainment (high, medium, and low), by citizenship (Germans vs. non-Germans), by urbanity, and by region (East vs. West). There is no evidence of any endogenous effect on either the extensive or the intensive labor-supply models when the model is estimated using fixed effects. Some of the neighborhood variables appear as statistically significant in the pooled least-squares specifications, but none are consistently so to warrant further discussion.

5.4 Discussion

The main conclusion that can be derived from the set of regression results is that the failure to account for unobserved heterogeneity can lead to grossly overestimated precision in the estimated impacts of neighborhood characteristics on female labor supply. Although the coefficients are more precisely estimated via pooled least squares (Tables 2 and 3), this estimator is not consistent in the presence of fixed effects that are correlated with unobserved individual and neighborhood attributes. While we are able to control for time-varying unobserved neighborhood characteristics by leveraging an important result from vertical sorting models, the individual-level fixed effects can still present problems for the estimation. Unobserved heterogeneity at the individual level can simultaneously impact the likelihood of locating in a good neighborhood and the conditional probability of employment, which will lead to an upward bias in the estimated effect of good neighborhood attributes. As it turns out, it also leads to an unwarranted increase in the precision of the estimator.

When we allow for the presence of unobserved heterogeneity that is correlated with residential choice and use a consistent approach such as the within estimator (Tables 4 and 5), we find no evidence for the presence of neighborhood effects at all. Since the identification of the effect is anchored on the changes over time within each unit, however, there is a considerable loss of precision in the estimation. Nonetheless, the coefficient estimates for the neighborhood characteristics are more robust to the incremental inclusion of covariates as opposed to the results obtained using pooled least squares, which are less stable.

There is no evidence that the "effect" for mothers are larger than for females in general. Although mothers are generally less attached to the labor market, being one does not impact

[20] An in-depth discussion is suppressed, but the results themselves are available from the authors upon request

on on labor-market participation as much as the number of young children. Similar to the result of Stoloff, Glanville and Bienenstock [1999], the presence of young children introduces a significant constraint for participation. In fact, the presence of children is the most robust and significant group of explanatory variables across most models, indicating that this is the most important factor that determines women's participation in the labor market.

For the extensive labor supply (Table 4, Column (6)), having children of any age between 0 to 14 decreases the likelihood of being employed, with the impact largest for children aged 0–3. In terms of the intensive labor supply (Table 5, Column (6)), each additional child aged 6–14 increases the likelihood of being in full-time employed conditional on being employed, while the number of children aged 0–6 does not seem to matter as much. The neighborhood characteristics themselves do not play a major role. In particular, the share of children in daycare does not appear statistically significant in the fixed-effects results.

These results are in line with Weinberg, Reagan and Yankow [2004] with one caveat. In their study which examines the impact of neighborhood attributes on the intensive labor supply, they find that even after accounting for individual unobserved heterogeneity, there is still a significant effect of neighborhood characteristics on labor-market activity. However, they note that estimation approaches that do not take into account selection "substantially overstate the social effects of neighborhoods" [Weinberg, Reagan and Yankow 2004, p. 904]. In our case, the correlation between the individual fixed effects and observed and unobserved neighborhood characteristics accounts for the entirety of the putative neighborhood impacts that the results from pooled least squares would suggest.

In contrast, Maurin and Moschion [2009] find a significantly positive effect of neighbor's labor-market participation on a mother's decision to participate in France. There are several potential explanations for the disparity in findings. First, there exist country-specific differences in gender-role attitudes and childcare utilization. While in Germany, especially in West Germany, the traditional role model still predominates and women are faced with relatively poorly developed childcare facilities and working-time models that are not flexible enough. France, however, is considered as a country where family and work reconcile better [Luci 2011; Dörfler 2007]. Thus, the participation rate of women aged 25–54 and the share of women working fulltime is larger in France than in Germany[21]. Given this information, one could

[21] Information retrieved from http://ec.europa.eu/eurostat/data/database.

argue that some German women who are willing to work are not able to find a job which can be reconciled with their family responsibilities.

Another potential source for the disparity in findings might be due to differences in the data samples and the definition of neighborhoods. Maurin and Moschion [2009] employ French data in which neighborhoods are defined as areas of about 20 adjacent households and which are restricted to mothers aged 21–35, living in two-parent families, and having at least two children. Their analysis is thus based on a much more homogeneous sample of individuals and their close neighbors who tend to share similar observed and unobserved characteristics. But compared to our German dataset, the French Labor Force Survey was not augmented with further neighborhood characteristics that might influence a mother's labor-market participation.

Regarding the identification strategy, Maurin and Moschion [2009] employ an instrumental-variable approach using the sex composition of the two eldest siblings in the neighboring family as an instrument. Using children's sex mix as an identifying instrument was first proposed by Angrist and Evans [1998], who estimated the effect of fertility on women's labor supply in the US. Under the presumption that parents have a preference for mixed-sex siblings composition, it exploits the idea that parents of same-sex siblings are more likely to have an additional child. However, apart from the issue of its strength as an instrument,[22] the validity of children's sex mix as a natural experiment is problematic since it imposes rather strong restrictions on preferences and household technologies [Rosenzweig and Wolpin 1998]. When applied to the neighborhood case, it is not always clear that the sex mix of the neighbors' children influences women's labor-market participation only through its impact on the neighbors' own participation decision.[23]

Our paper corroborates evidence obtained elsewhere that neighborhood quality and peer characteristics do not have a substantial impact on adult labor-market outcomes.[24]. The MTO

[22] Daouili, Demoussis and Giannakopoulos [2009] demonstrate the weakness of this instrument as applied in the sample of Greek mothers.

[23] In a robustness check, Maurin and Moschion [2009] reevaluate the neighborhood effects on a mother's labor-market participation using the distribution of children's quarter of birth as an instrumental variable. But the validity of this instrument has often been questioned by other researchers as well (see, for instance, Bound, Jaeger and Baker [1995], Bound and Jaeger [2000], and, more recently, Fan, Liu and Chen [2014]).

[24] Quasi-experimental evidence for student outcomes also do not show that there is any significant peer effect. See the following: Lavy, Silva and Weinhardt [2012], Gibbons, Silva and Weinhardt [2013], and Weinhardt [2014]. Using the expulsion of scientists that occured under Nazi-ruled Germany, Waldinger [2012] also find no evidence of peer effects on the productivity of researchers.

program, which provides evidence from an experimental setting, did not result in improved earnings or educational attainment [Katz, Kling and Liebman 2001; Kling, Liebman and Katz 2007] although there is some evidence that it improved health outcomes [Ludwig et al. 2011]. In a quasi-experimental setting involving housing in Toronto, Oreopoulos [2003] shows that the neighborhood quality experienced as a child does not significantly impact a number of outcomes, including the likelihood of unemployment. Damm [2014] uses exogenous variation generated by a natural experiment in Denmark to show that labor-market outcomes are not affected by the neighborhood employment rate and the neighborhood skill level, which is similar to our results for aggregate human capital as measured by the share of highly educated people.[25] Indeed, Angrist [2014, p. 98] notes that "compelling evidence" arising out of research designs with exogenous manipulation of peer characteristics "have mostly uncovered little in the way of socially significant causal effects."

Notably, ours is the first paper based on observational data that matches the conclusions derived from experimental and quasi-experimental settings. Using observational data without accounting for the selection bias arising out of the double heterogeneity of unobserved neighborhood and individual characteristics, one can derive significant statistical relationships between observed neighborhood characteristics and individual-level labor-market outcomes. We emphasize that this could be the result of nonrandom sorting, but Angrist [2014] shows that these relationships can arise as well merely because of a mechanical statistical relationship in the absence of a genuine exogenous change in neighborhood characteristics. In our case, we demonstrate that when heterogeneities are taken into account, none of the estimated "effects" survive, which is in agreement with what is considered to be compelling evidence from (quasi-)experimental settings.

6 Conclusion

Using a unique dataset that combines information on individuals from the SOEP with information from administrative social security data and real-estate information from the internet platform *ImmobilienScout24*, we investigate the effect of neighborhood characteristics on the individual labor supply of women aged 25–60 years in Germany. Nonrandom sorting and

[25] There is evidence, however, that information is transferred along ethnic lines [Damm 2014].

unobserved heterogeneity at the individual and neighborhood levels make recovering these impact parameters more complicated in the absence of (quasi-)experimental variation in neighborhood attributes. Our estimation strategy rests on using a hedonic pricing model to control for time-varying neighborhood-level unobserved heterogeneity and using a fixed-effects approach to account for the correlation induced by individual time-invariant unobservables.

The benchmark results suggest that women's participation behavior is significantly associated with peer and neighborhood attributes. In particular, the extensive margin is driven by the average female employment rate while the intensive margin is driven by the average share of full-time employed in the neighborhood. These associations are stronger in the subsample of mothers, who are less attached to the labor market. Using a fixed-effects approach to capture individual time-invariant unobservable heterogeneity, we find no significant effect of neighborhood characteristics on the extensive and intensive labor supplies.

In light of the ongoing demographic transition and the consequent pressure it imposes on developed countries' public finances, particularly in Europe, there is now a recognized impetus to increase the labor-market participation of certain subgroups of the population, especially women and older workers, who are generally able and often willing to work. The old-age dependency ratio, defined as the ratio of "older" people to the working-age population (in percent),[26] was at 28.4 percent in 2010 and is projected to increase to 58.5 percent by 2060 [EC 2010]. If nothing else changes, this trajectory is expected to destabilize the pension system.[27] While female labor-force participation (LFP) is already quite high (nearly 70 percent in EU-15, EU-27, and OECD countries for women aged 25–64 years in 2010 [OECD 2012]), there is still a nontrivial gap between men and women, with more women in part-time work [EC 2010]. In Germany, in particular, men's LFP rate is 88.2 percent while women's is 75.2 percent—a difference of 13 percentage points.

Policies that encourage the participation of women in the labor market is a critical element of the set of instruments to manage the demographic transition. These include, for example, child-related leave entitlements and the provision of childcare services, tax benefits and direct

[26] More accurately, the dependency ratio here is "expressed in terms of the relative size of the young (0–19 years) or/and of the old (65 and over) population to the working-age population (20–64), instead of the common definition, which considers the 0–14 years as young population and 15–64 years as working-age population. This adjustment is made on [the] grounds that, in the EU-27's Member States, most people aged 15–19 are still in education, and few of them are in paid work." [EC 2010, p. 61]

[27] In Bachmann et al. [2013], projections based on various scenarios pertaining to the labor-market participation of older workers in Germany are calculated.

subsidies, as well as anti-discrimination legislation. At the same time, closing the gap between male and female participation rates addresses a core principle of the EU, which is the fundamental right to equality between men and women as enshrined in Article 2 of the Maastricht Treaty. In 2010, the European Commission adopted a Women's Charter where the principle of "equal economic independence," among others, shall underpin the actions of the EC. In the Charter,[28] the EC "reaffirms [its] commitment to ensure the full realisation of women's potential and the full use of their skills, to facilitate a better gender distribution on the labour market and more quality jobs for women." Our results suggest that the set of policies that mitigates the impact of having children would bear the most fruit.

One could argue that policies which address a particular group can have spillovers to groups who were not originally targeted. The policy prescription arising out of such a network model invites a concentration of interventions within, say, a neighborhood, and then relying on the social multiplier to self-propagate the benefits of the intervention. However, the evidence for the existence of a social spillover is overstated. While a number of observational studies have demonstrated a statistically significant correlation between the labor-market outcome of one's neighbors (along with other neighborhood characteristics) and one's own outcomes, the evidence obtained from (quasi-)experimental settings does not support the idea that there is any active causal link between neighborhood variables and individual outcomes. By controlling for unobserved heterogeneity, the present manuscript substantiates the more compelling experimental evidence. Policies should be designed, therefore, with the knowledge that peer or neighborhood effects are not likely to materialize at least for adult female labor-market outcomes.

[28] Available here: <http://goo.gl/c4rrXJ>.

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Appendix A Tables

TABLE A.1
SUMMARY STATISTICS FROM THE SOEP AND IAB DATASETS

Variable	Mean	Std. Dev.	Min.	Max.
Individual characteristics				
Employed	0.75			
Employed in full-time job	0.52			
Age	44.82	9.37	25	60
Age, squared (÷ 1000)	2.096	0.822	0.625	3.60
Low education	0.14			
Medium education	0.57			
High education	0.29			
Married	0.72			
German citizen	0.85			
No. of children (aged 0–3)	0.09	0.32	0	3
No. of children (aged 3–6)	0.11	0.33	0	3
No. of children (aged 6–14)	0.36	0.66	0	4
No partner in household	0.21			
Partner employed	0.66			
Partner unemployed or inactive	0.13			
Partner's income (÷ 1000)	1.71	1.83	0	30
Neighborhood characteristics				
Female employment rate	92.94	3.45	71.87	98.48
Share of women in full-time employment	52.5	5.86	38.93	74.72
Share of foreigners	8.97	6.25	0.52	46.65
Share of highly educated	9.64	5.60	1.51	41.06
Share of children (aged 0–3) in daycare	17.26	11.73	2.6	60.71
Share of children (aged 3–6) in daycare	91.05	4.24	70.5	100

NOTES.—The number of observations is 10,959 except for the indicator variable for female labor supply and the share of women in full-time employment. This variable is conditional on being employed, which reduces the number of observations to 7,959. Neighborhood characteristics are expressed in percent. The standard deviation and minimum and maximum values of binary indicators are not presented.
SOURCE.—Authors' calculations based on SOEP and IAB. Individual characteristics come from the SOEP while neighborhood characteristics are from the IAB. The neighborhood is defined at the postcode level.

TABLE A.2
SUMMARY STATISTICS FROM IMMOBILIENSCOUT24

Variable	Mean	Std. Dev.	Min.	Max.
(log) Price	12.46	0.61	9.21	19.73
Age	38.33	31	0	140
Age, squared ($\div$ 1000)	2.43	3.35	0	19.6
Age, cubed ($\div$ 1000)	190.9	366.52	0	2744
(log) Size (sq. m.)	5.07	0.42	3.22	18.42
Has cellar	0.52			
State: Like new / first move-in	0.18			
State: Renovated	0.05			
State: Modernized, well-kept	0.33			
State: Not renovated or not stated	0.44			
Type: Single detached	0.39			
Type: Multi-storey	0.09			
Type: Farmhouse, bungalow, villa, special	0.07			
Type: Terrace, terrace-middle	0.11			
Type: Terrace-end	0.05			
Type: Semi-detached	0.16			
Type: Other	0.12			

NOTES.—The number of observations is 376,814. The standard deviation and minimum and maximum values of binary indicators are not presented.
SOURCE.—Authors' calculations based on *ImmobilienScout24*.

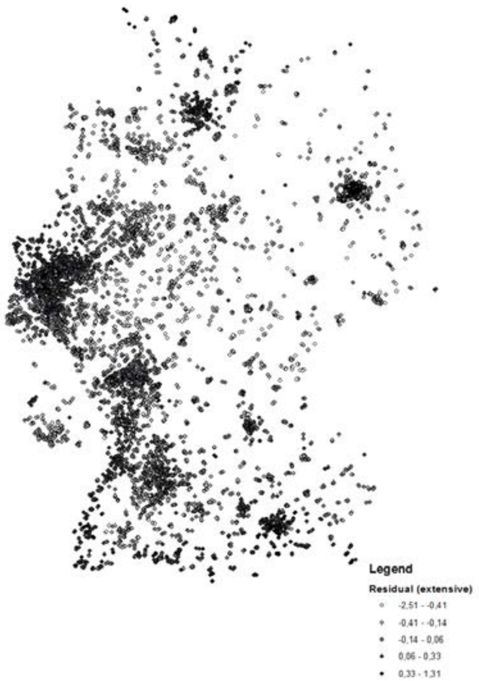
TABLE A.3
HOUSE PRICE REGRESSIONS

	Extensive (1)	Intensive (2)
Age	-0.00235***	-0.00141***
	(0.000553)	(0.000530)
Age, squared (÷ 1000)	-0.0478***	-0.0744***
	(0.0118)	(0.0114)
Age, cubed (÷ 1000)	0.000292***	0.000434***
	(0.0000719)	(0.0000709)
(log) Size (sq. m.)	0.797***	0.786***
	(0.0141)	(0.0147)
Has cellar	0.0268***	0.0204***
	(0.00614)	(0.00657)
State: Renovated	0.0430***	0.0436***
	(0.00822)	(0.00803)
State: Modernized, well-kept	-0.0349***	-0.0319***
	(0.00578)	(0.00605)
State: Not renovated or not stated	-0.102***	-0.0914***
	(0.00655)	(0.00649)
Type: Single detached	0.0808***	0.0869***
	(0.00626)	(0.00605)
Type: Multi-storey	-0.141***	-0.144***
	(0.0141)	(0.0151)
Type: Farmhouse, bungalow, villa, special	0.246***	0.246***
	(0.00947)	(0.00932)
Type: Terrace, terrace-middle	-0.0893***	-0.104***
	(0.00657)	(0.00665)
Type: Terrace-end	-0.0389***	-0.0515***
	(0.00742)	(0.00748)
Type: Other	-0.0486***	-0.0542***
	(0.00907)	(0.00885)
Female employment rate	0.0250***	
	(0.00370)	
Share of foreigners	0.0272***	0.0201***
	(0.00160)	(0.00139)
Share of highly educated	0.0381***	0.0397***
	(0.00204)	(0.00211)
Share of children (aged 0–3) in daycare	0.00260	-0.00346
	(0.00195)	(0.00224)
Share of children (aged 3–6) in daycare	-0.00787*	-0.00346
	(0.00401)	(0.00479)
Share of women in full-time employment		0.0151***
		(0.00246)
Constant	6.300***	7.655***
	(0.379)	(0.445)
Observations	376814	376814
R^2	0.687	0.686

NOTES.—The reference category for the state indicators is “like new / first move-in”; for the type indicators, it is “multi-detached”. Indicators for the observation year are included. Standard errors are robust to clustering at the postcode level and are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE.—Authors’ calculations based on *ImmobilienScout24* and IAB.

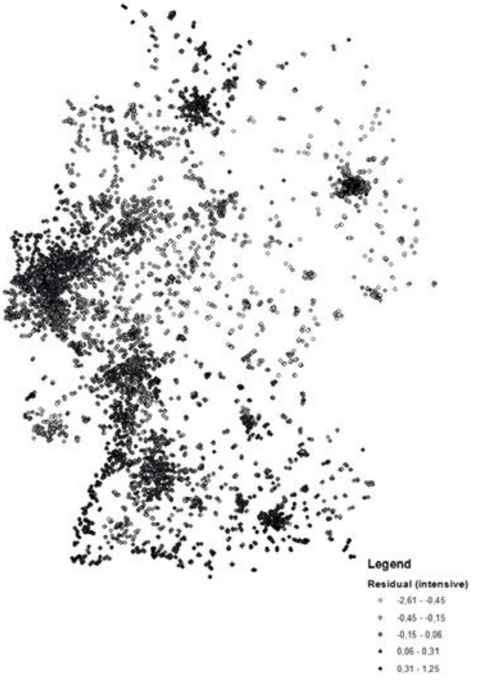
Appendix B Figures

FIGURE 1
RESIDUALS FROM HEDONIC HOUSE PRICE REGRESSION (EXTENSIVE LABOR SUPPLY)



SOURCE.—Authors' calculations based on *ImmobilienScout24* and IAB.

FIGURE 2
RESIDUALS FROM HEDONIC HOUSE PRICE REGRESSION (INTENSIVE LABOR SUPPLY)



SOURCE.—Authors' calculations based on *ImmobilienScout24* and IAB.