Ifo Institute for Economic Research at the University of Munich

Ifo Working Papers

The Determinants of Joint Residential and Job Location Choices: A Mixed Logit Approach

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Ifo Working Paper No. 82

December 2009

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Abstract

This paper empirically investigates the household's decision to reside and work either in the central metropolitan area, or in the surrounding nonmetropolitan area, or to commute between the two regions. As economic theory suggests the location decision amounts to trading off wages, housing costs, and commuting time. A mixed logit model is employed to quantify the interaction effects of these economic factors in the joint residential and job location choice. The empirical approach does not rely on the restrictive IIA assumption and allows for arbitrary correlation patterns between coefficients. Using data from a recent survey of more than half a million German households, the elasticities of individual location choice with respect to wages, housing costs, and commuting time are estimated. The results show that individual valuations of these factors are of the expected signs but vary substantially in the population. Shifts in consumer surplus and in the spatial distribution of households that are associated with changes in the determinants of location choice are calculated based on the empirical estimates.

JEL Code: R23, R12, C15, C25.
Keywords: Location choice; commuting; metropolitan area; discrete choice models; mixed logit; simulation based estimation.

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1 Introduction

The daily commute is an understood part of the job for the vast majority of people in the workforce. Strictly speaking, everybody who does not work at home is a commuter. The individual's decision on the extent of her daily commute is thereby inextricably linked to the decisions on where to live and where to work, respectively. Apparently, the non-separate choices on residence, job location, and the daily commute lead to a huge variety of outcomes in reality. The extent of commuting we can observe ranges from a three-minutes walk down the street to a three-hour trip. Commuting trips may take place within the community of residence or across the borders of communities, counties, federal states, or even countries. The magnitudes involved with commuting are thereby substantial in many dimensions. Following the most general definition of commuting, 85% of German employees considered themselves to be commuters in 2004.[1] The share of in-commuters among employees at the community of work was 37% in Germany in 2003.[2] Moreover, about 17% of commuters in Germany travel more than 25 km and five % more than 50 km one-way to their place of work.[3] The phenomenon is of course not restricted to Germany as the OECD statistics suggest: "Between one and 16% of the employed in OECD countries commute between regions every day."[4]

The typical picture one bears in mind when thinking about the issue is that people live in suburbs and commute to an urban center, where all the work is located at the central business district (CBD). This view of the "monocentric city" has been formally described and analyzed in the seminal works of Alonso (1964), Muth (1969), and Mills (1972). Although in reality production is of course not exclusively located at the city centers, Figure 1 illustrates that the assumption of monocentricity is a fairly good approximation of the structure of the labor markets constituted by many German cities. The map shows detailed commuting patterns in Germany. In numerous cases like Berlin, Hamburg, Munich, etc., there is a dominant center which attracts employees from a large surrounding area. All economic models in the Alonso-Muth-Mills tradition share certain

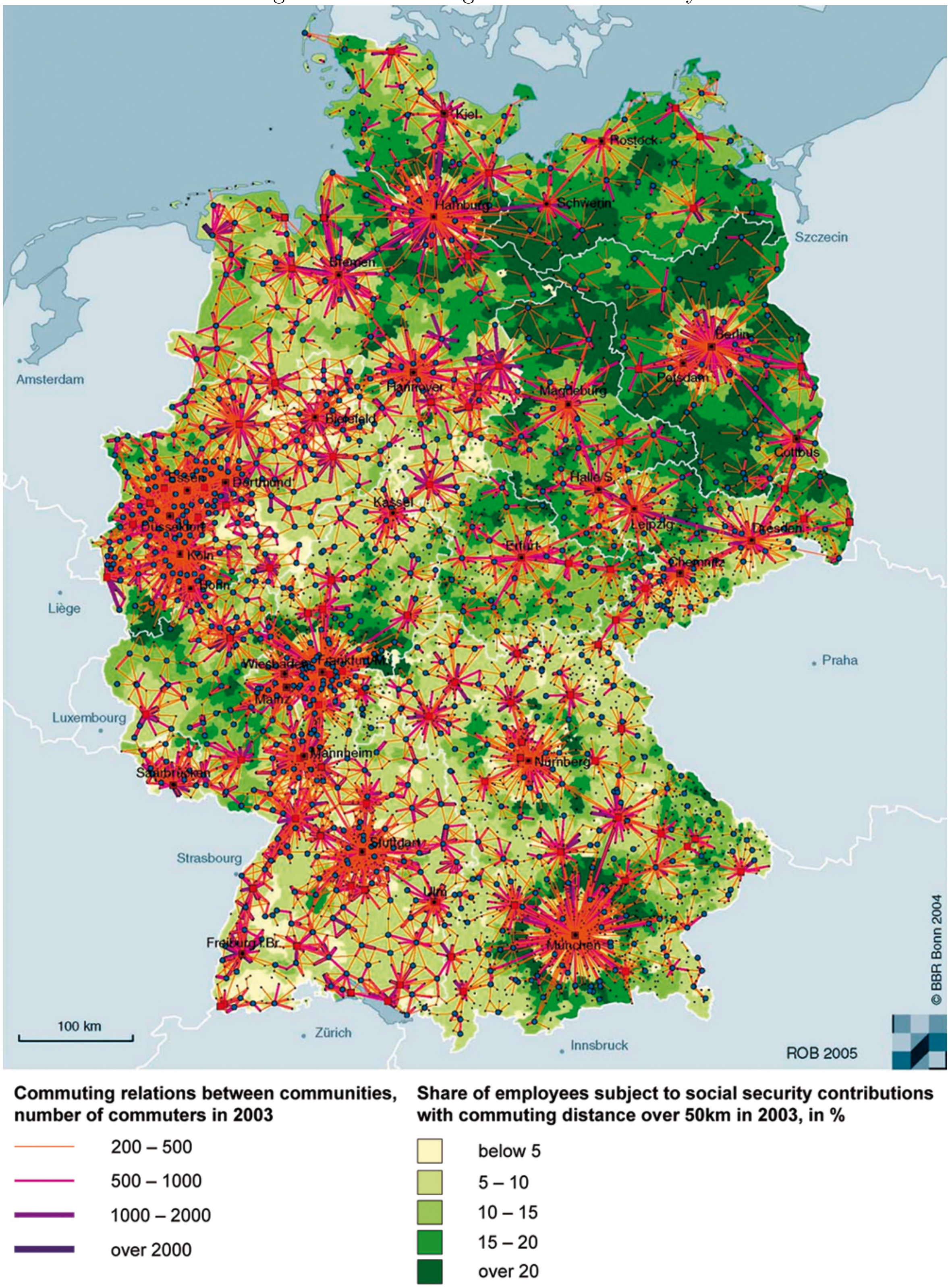
[1]See Statistisches Bundesamt, 2005.

[2]Figures from the Federal Employment Office.

[3]See Statistisches Bundesamt, 2005.

[4]See OECD, 2005.

Figure 1: Commuting Patterns in Germany



Source: BBR (2005)

basic insights, regardless of whether the production is located only at the city center or also at other points in space ("polycentric cities"). The individual location choice in this kind of models is determined by trade offs between wages, housing costs, and the economic cost of commuting. Besides these economic factors, the literature emphasizes the role of amenities and the local quality of life in the household's location choice.[5] Common to all these studies is the economic view that in equilibrium all the relevant factors balance out, such that utility is equal across locations and/or choices.[6] Interestingly, the more recent new-economic-geography literature by and large ignores the phenomenon of commuting and consequently treats place of residence and place of production as the same (e. g. Krugman, 1991). There are, however, exceptions like the works of Krugman and Livas-Elizondo (1995), Tabuchi (1998), Murata and Thisse (2005), Tabuchi and Thisse (2005), and Borck et al. (2007). The just mentioned strand of literature appropriately emphasizes the role of industry location for the formation of commuting patterns. I will focus on the determinants of location decisions of individuals only, who arguably take the locations of possible employers as given.

According to economic theory, local wages, housing costs, and the cost of commuting represent the three most important economic determinants of the household's location decisions. The objective of this paper is to provide a comprehensive approach to empirically quantify the impacts of all three factors and their interactions in individual location choice. To theses ends, I exploit an extensive individual-level data set containing information on individual choices of residence and work location, commuting time, and individual characteristics. Augmenting these figures with county-level data on wages and housing costs, I estimate the underlying preferences that govern individual location choices. Discrete choice models have been widely used to analyze the determinants of the location choice of households. For example, Quigley (1985) or Nechyba and Strauss (1998) focus on the role of public services. Recent advances include Schmidheiny (2006) and Bayer et al. (2007), who are concerned with issues of sorting. Most of this literature looks at the choice of community, school district, or neighborhood. In contrast, the present analysis follows the idea of So et al. (2001) to focus on the relationship between the metropolitan area and its surrounding nonmetropolitan

[5]The pioneering works being those of Rosen (1979) and Roback (1982); see Blomquist (2006) for recent developments.

[6]However, Frey and Stutzer (2008) cast serious doubts on this strong notion of equilibrium.

area. In their analysis, the choice set boils down to four alternatives: (1) To live and work in the CBD, (2) to live and work in the nonmetropolitan area, (3) to live in the nonmetropolitan area and work in the CBD, or (4) to live in the CBD and work in the nonmetropolitan area, respectively. The object of their study is the metropolitan area of Des Moines, Iowa, and the surrounding nonmetropolitan area. While adopting their modeling of the choice set, I apply it to a richer set of data which provides improved preconditions for the estimation. On the one hand, the data provides the relevant information on all labor market-regions in Germany instead of only one, allowing me to focus on the three largest cities, i. e. Berlin, Hamburg, and Munich. On the other hand, the households' counties of residence and work are identified in the data, such that regional figures can be assigned to the alternatives that have not been chosen. This means, in particular, that reliable information on the counterfactual outcomes of individual decisions is available.

For the purpose of estimation, I employ a mixed logit model where coefficients are allowed to vary randomly over decision makers, instead of being constant.[7] Train et al. (1987) and Ben-Akiva et al. (1993) are early works applying this method. Improvements in computer speed have led to an increasing use of such simulation based models of discrete choice, for instance in Bhat (1998) and Brownstone and Train (1999). This empirical model is particularly appropriate in the present context as it elegantly sidesteps some issues involved with classic multinomial logit estimation. Depending on the exact situation to be analyzed, individual location choice typically is at odds with the restrictive "independence of irrelevant alternatives" (IIA) assumption that is implicit in logit models. Most of the above mentioned studies make use of nested structures to address this problem.[8] The mixed logit model employed here does not rely on the IIA assumption. It further accommodates the hierarchical structure of location choice, given that three different labor market-regions are at scrutiny. More precisely, households are assumed to first choose a labor-market region. Then, they decide on one of the four combinations of the location of job and residence in the (non)metropolitan area, given the choice of labor market. This is an analogous proceeding to the nested models mentioned before. Moreover, I allow for arbitrary correlation patterns in the

[7]This approach is also known as "random coefficients logit" or "error components logit." See Train (2003) for an excellent introduction.

[8]A very illustrative example is Quigley (1985). He considers the household's location choice in three stages: Choice of dwelling given the choice of neighborhood and town, choice of neighborhood given choice of town and finally the choice of town.

estimation of coefficients. This approach explicitly addresses the problem that utility might be correlated over the four alternatives within each labor market, given the modeling of the choice set. The estimation results clearly confirm the predictions of economic theory with respect to the important roles of wages, housing costs, and commuting costs in the individual location decision. Moreover, the findings indicate a considerable degree of variation in the households' valuation of commuting- and housing costs. The estimation results are converted to elasticities to show how changes in wages, housing costs, or commuting time affect the distribution of households between metropolitan and nonmetropolitan areas. Accordingly, no systematic differences in the magnitude of the impacts between the three factors are found. Further results include the calculation of changes in consumer surplus induced by changes in the explanatory variables.

The remainder of the paper proceeds as follows. The next section briefly outlines the underlying economic theory. In section 3 the empirical setting and the data are described before the econometric specification is illustrated in detail. Section 4 presents the results from the mixed logit estimation, the implied elasticities, and results on consumer surplus. Section 5 discusses quantitative implications of the results on the basis of two hypothetical scenarios. Section 6 concludes.

2 Theory

In order to briefly illustrate the economic theory that underlies the empirical analysis, this section develops a simple model of household preferences and location choice.

2.1 Household Preferences

Regions are assumed to consist of a metropolitan area and a surrounding nonmetropolitan area. The political borders of the central area are the outcome of historical processes and are therefore considered as given. Each of the two areas i is characterized by a bundle of local attributes, A_i, and a competitive local housing market where the local price of housing, p_i, is determined. In addition, in each area a numeraire good, z, is produced with labor as the only input. Assume that z can be shipped costlessly within (and across) regions. Thus, each area hosts a local labor market, j, where the wage rate, w_j, is determined.

The preferences of households are described by a standard utility function

$$U(z, h, A),$$

where h is the consumption of housing. Households choose a residential location i, thus facing the local attributes A_i and the local cost of housing, p_i. They also choose a job location j, where the prevailing wage w_j is earned. If $i \neq j$, commuting costs of t_{ij} have to be incurred. Therefore, each household faces a budget constraint:

$$p_i h + z + t_{ij} \leq w_j. \tag{1}$$

Utility maximization subject to (1) yields the indirect utility function

$$U(z^*, h^*, A_i^*) := V\left(w_j, p_i, t_{ij}; A_i\right) \quad i, j = M, N, \tag{2}$$

where M and N refer to the metropolitan and the nonmetropolitan area, respectively. It directly follows that

$$\frac{\partial V}{\partial w} > 0, \frac{\partial V}{\partial p} < 0, \frac{\partial V}{\partial t} < 0. \tag{3}$$

These derivatives are the main determinants of the elasticities of the household's location choices that are to be estimated in section 4.

Local attributes may have a positive or a negative effect on utility, depending on their nature as an amenity or disamenity: $\frac{\partial V}{\partial A} \lesseqgtr 0$. This model does not include the descriptions of housing supply, the production side or the equilibrium concept. Such a full general equilibrium model is not required in the context of this paper as it focuses solely on the household's location decision.

2.2 Location Choice

Households simultaneously choose a residential and a job location to maximize utility. This requires that the chosen alternative is at least as good as all other possible alternatives:

$$V\left(w_{j^*}, p_{i^*}, t_{i^*j^*}; A_{i^*}\right) \geq V\left(w_j, p_i, t_{ij}; A_i\right) \quad \forall i \neq i^* \; j \neq j^*. \tag{4}$$

A close look at condition (4) reveals some interesting predictions of the model, as stated by So et al. (2001):

Prediction 1 *Households residing at i and working at j (commuters) demand higher wages than their non-commuting neighbors living at i and working at i.*

This follows directly from (3) and (4) as both types of households face the same housing cost and amenity endowment, but commuters incur higher commuting costs.

Prediction 2 *The wage gap between locations i and j is increasing in commuting costs t_{ij}.*

This is a straight forward extension of Prediction 1, since higher wages compensate households for higher commuting costs.

Assume that the price for housing at $i = M$ exceeds that at $i = N$[9] and that commuting costs are the same in both directions, i. e. $t_{ij} = t_{ji}$. Under this assumption, we have:

Prediction 3 *Average wages demanded in the metropolitan area will exceed average wages demanded in the nonmetropolitan area as long as the utility differences induced by different local amenity bundles do not offset the monetary utility differences induced by the cost of housing.*

To see this, consider two households residing at $i = M$ and $i = N$, respectively. Under the given assumption and without commuting, the household living at M will demand a higher wage, w_M

[9] This is most likely the case at the metropolitan area as prices are bid up due to higher population density.

for condition (4) to hold. For commuters from N to M the wage at M has to be higher than at N, following Prediction 1. By the same prediction, there is only one group that requires wages in the low housing-price location N to exceed those at M: Households who commute from M to N. Prediction 3 for average wages follows from this.

3 Empirical Approach

This section describes the empirical setup and the data used for the empirical analysis of the household's residential and job location choice specified in section 2. The estimated empirical model is derived in detail in subsection 3.2.

3.1 Setting and Data

Given the focus on the relation between the metropolitan area and the surrounding nonmetropolitan area, individuals select one of four possible alternatives within their labor-market region to maximize utility:

MM: Live in the metropolitan area, work in the metropolitan area

MN: Live in the metropolitan area, work in the nonmetropolitan area

NN: Live in the nonmetropolitan area, work in the nonmetropolitan area

NM: Live in the nonmetropolitan area, work in the metropolitan area

It is assumed, that this choice is made given the prior choice of the labor-market region. The first choice is explicitly included in the empirical model, such that a nested structure with a total of 12 alternatives[10] obtains.

[10]First, the choice between the three labor-market regions, second the choice between the four alternatives MM, MN, NN, NM within the chosen labor-market region.

Objects of investigation are three labor market-regions ("Raumordnungsregionen") in Germany, which all exhibit an explicit center–periphery structure. In particular, the study focusses on the labor markets of the three biggest German cities: Berlin, Hamburg, and Munich.[11] As Figure 2 illustrates, these regions consist of a central urban county (the metropolitan area) and various less densely populated surrounding counties that constitute the associated nonmetropolitan area.[12] Comparison of Figures 1 and 2 shows that the chosen administrative units correspond very well to the actual labor markets constituted by the three cities. Individual-level data on commuting time, location of residence and job, age, education, children, and household income are taken from the "Perspektive Deutschland" study 2004, a large survey among more than half a million Germans. It reports opinions and valuations of German residents concerning a variety of aspects of life in Germany and the German regions, respectively. Representativeness is ensured by sampling weights drawn from a parallel field-survey with more than 10,000 participants.[13] Monthly net household income in € is reported net of taxes and including transfers. I focus on full-time employed individuals only in order to ensure a certain degree of homogeneity of decision makers and of the driving forces behind their decisions. Since the analysis scrutinizes wages and commuting behavior, this is a sensible restriction of the sample.

Commuting cost is proxied for by commuting time. However, as individual commuting time is naturally reported for the chosen alternative only, the respective values for the other three alternatives are missing. This problem is solved by estimating commuting time for each of the four alternatives within one labor market region. In addition, this approach sidesteps any endogeneity issues that might arise because wages, commuting time, and housing cost are chosen simultaneously in the location decision. Individual commuting time (in minutes, one way) for each alternative a in each

[11]See Appendix A for the exact listing of counties that constitute the respective (non)metropolitan areas.

[12]As Figure 1 shows, there are many more labor market-regions with a similar structure in Germany. I choose the largest three, because of the high number of observations. Unfortunately, the numerically demanding estimation procedure does not allow for the inclusion of more labor market-regions. However, simple multinomial logit estimations including all labor market-regions with a center–periphery structure yield qualitatively similar results.

[13]See Fassbender and Kluge (2006) for an overview of the project.

Figure 2: Labor Market Regions of Berlin, Hamburg, Munich

labor-market region k is therefore predicted by the linear equation:[14]

$$t_{n,a_k} = \lambda_0 + \lambda_1 age_{n,a_k} + \lambda_2 edu_{n,a_k} + \lambda_3 sex_{n,a_k} + \lambda_4 married_{n,a_k} + \lambda_5 kids_{n,a_k} + e_{n,a_k},$$

with n indexing households, $a = MM_k, MN_k, NN_k, NM_k$ indexing alternatives, and $k = Berlin, Hamburg, Munich$ indexing labor market-regions. $kids$ is a dummy variable indicating if there are children aged between one and 16 years in the household. edu gives the years of schooling associated with the highest degree achieved. age is reported in categories that each subsume five years of age.

Wages are taken from the regional sample of employees (*Beschäftigtenstichprobe*) of the Institute for Employment Research (IAB). These data constitute a two percent random sample of all German employees subject to social security contributions and report individual daily wages in €.[15] I merge the detailed individual wage information of this data with the survey data by age, gender, education level, and type of job. Thus, I assign the average wage of people of the same age, gender, education level, and type of job who chose the same alternative a in the same labor-market region k to the respective alternatives faced by the individual.

The third important determinant of the location decision is housing cost. The regional statistical offices provide data on the average prices for land in 2001 – 2004 in € per sqm at the county level, which serve as excellent indicators for the local cost of housing. However, in this context it is important to consider not only the price but also the quantity of housing space consumed.[16] Unfortunately, exact information on the individual demand for living space is not available. Therefore, I use the reported number of adults and children in each household along with official figures on average housing demand of one- (two-, three-or-more-) person households to proxy for the desired housing space of a household.[17] A further straight forward prediction from theory is that the

[14]Least squares estimation and prediction account for the survey weights reflecting individual sampling probabilities.

[15]See Drews (2008) for a detailed description of the data.

[16]The monocentric city model predicts an inverse relationship between the demand for housing space and the price for housing.

[17]The figures stem from the German Statistical Office. Accordingly, the average housing space consumed by a one-person household in Germany in 2004 is 67.5 sqm (93.2 sqm for a two-person household, and 113.4 sqm for three-or-more-person households).

Table 1: Sample Means by Alternatives a^a

Variable	$a =$ MM	$a =$ MN	$a =$ NN	$a =$ NM	MM, MN	NN, NM
Location specific						
Commuting Time	30.6	37.6	25.3	47.3	31.1	33.1
Housing Cost	14.4	23.8	7.80	6.09	15.1	7.19
Wage	96.1	92.9	85.7	98.4	95.8	90.2
Individual						
Age	40-44	40-44	40-44	40-44	40-44	40-44
(Age Category)	(6.90)	(6.52)	(6.65)	(6.93)	(6.87)	(6.75)
Children	.211	.186	.306	.315	.209	.309
Education	11.6	11.8	10.8	11.1	11.6	10.9
Observations	20724	1865	8645	5634	22589	14279

Individual figures weighted by individual sampling probabilities.
[a]: Aggregated over all three labor market-regions k.

demand for housing varies with income. Thus, the housing cost of each alternative is divided by the household income that is reported in the "Perspektive Deutschland" data. Thus, individual housing cost is calculated as

$$p_{n,a_k} = \frac{L_{a_k} h_n}{y_n},$$

where L_{a_k} denotes the average land price for alternative a in labor-market region k, h_n denotes the demand for housing of household n, and y_n is the reported household income net of taxes and including transfers. Note, that the household income variable includes capital income and therefore differs substantially from the wage variable. This way of constructing the housing cost variable ensures that the empirical analysis measures the valuation of housing cost of people having roughly the same demand for housing and the same level of income.

Table 1 reports summary statistics of the sample by alternatives a and aggregated over all three labor markets k.[18] The facts are as expected. Wages are higher for people working in metropolitan areas and housing costs in the center widely exceed those in nonmetropolitan regions, even though the latter are corrected for individual housing demand and income. Interestingly, the theoretical predictions are confirmed only partly by the descriptive statistics. In line with theory, average wages are higher for those who commute from the suburbs to the center compared to wages of non-commuters who reside in nonmetropolitan areas. In addition, wages for commuters to the metropolitan area are slightly higher than those of residents. However, the average numbers do not show such mark-ups for commuters living in the metropolitan area over the wages of their non-commuting neighbors. Commuting time is, of course, much higher for the alternatives that involve commuting. On average, individuals who chose different alternatives do not differ substantially in age. The average age for each alternative lies in the category of people aged $40 - 44$ years. Furthermore, people who live in the center exhibit a higher amount of years of schooling and are less likely to have children.

3.2 Econometric Specification

The objective of this paper is to estimate the influence of wages, housing costs, and commuting time on the household's simultaneous choice of residential and job location. The theoretical model on location choice outlined above naturally gives rise to estimation based on a random utility maximization (RUM) model. This sort of discrete choice models has its foundations in the seminal work of McFadden (1973). More precisely, I adopt the so called "random coefficients logit" approach where coefficients are allowed to vary over decision makers.[19] In this case, a household chooses a combination of residence and working place among the four alternatives a ($a = MM_k, MN_k, NN_k, NM_k$) which each are located in one of the labor market regions k ($k = Berlin, Hamburg, Munich$). Note, that this setting implies a nested approach, where the individual chooses one alternative a after having decided to work and reside in labor market-region (i. e. nest) k. In the following, I

[18] Summary statistics for each single labor-market region are presented in Tables A.1, A.2, and A.3 in Appendix B.

[19] This approach is also known as "mixed logit" or "error components logit" and has been applied in many studies, e. g. Bhat (1998), Brownstone and Train (1999), or Train (1998). For an excellent introduction, see Train (2003).

suppress the subscript k for convenience, as each element that varies over a also varies over k. The indirect utility that household n derives from choosing alternative a is

$$\widetilde{V}_{n,a} = V_{n,a} + \varepsilon_{n,a}, \tag{5}$$

where $V_{n,a}$ is the deterministic part of indirect utility, which depends on observable characteristics of households and alternatives, and $\varepsilon_{n,a}$ is an unobserved random term that is identically and independently drawn from an extreme value type I distribution. Analogously to equation (4), the household chooses alternative a^* if and only if

$$\widetilde{V}_{n,a^*} \geq \widetilde{V}_{n,a} \quad \forall a \neq a^*. \tag{6}$$

The choice of factors that influence the deterministic part of indirect utility is guided by the theoretical model. According to considerations about the distribution of tastes for these factors in the population, $V_{n,a}$ can be written as:

$$V_{n,a} = \alpha X_{n,a} + \beta_n Z_{n,a}, \tag{7}$$

where the tastes for the factors contained in $X_{n,a}$ are assumed to be constant across households, while those contained in $Z_{n,a}$ are assumed to vary randomly over households. Note in this context, that the vector of coefficients β is subscripted with n while α is not.

In the most general form of equation (7),

$$X_{n,a} = age_n \iota^{com} + kids_n \iota^{com} + edu_n \iota^{com} + age_n \iota^M + kids_n \iota^M + edu_n \iota^M + w_{n,a}, \tag{8}$$

where ι^{com} is an indicator variable for people who commute (i. e. $a = MN, NM$), and ι^M is an indicator of people who live in the central metropolitan area of their respective labor market-region (i. e. $a = MM, MN$), and

$$Z_{n,a} = \delta^a + \delta^k + p_{n,a} + t_{n,a}, \tag{9}$$

where δ^a represents a vector of fixed effects for each alternative $a = MM, MN, NN, NM$, and δ^k represents a vector of fixed effects for each labor-market region $k = Berlin, Hamburg, Munich$.

The influence of the determinants of choice contained in $X_{n,a}$ is assumed to be constant across households. The indicator variables ι^{com} and ι^M are designed to capture that the households' tastes for living in the center or for commuting might systematically vary with individual characteristics like age, children, or education.[20] Furthermore, including wages in $X_{n,a}$ amounts to assuming that individual tastes for wages are identical among households.[21]

In contrast, the coefficients of the variables in $Z_{n,a}$ are assumed to vary randomly over households. For example, the individual tastes for commuting costs in the population, expressed by the coefficient β^t_n, are assumed to follow a lognormal distribution with parameters θ to be estimated. This distribution is also called the mixing distribution. Adopting such a specification accounts for two issues. First, the coefficient on commuting time is expected to be negative in the entire population as it is associated with a cost. Thus, the negative of commuting time is used in estimation such that its lognormal distribution ensures that the coefficient is negative for each individual. Second, even as commuting is generally disliked, there might still be substantial unobserved variation in personal tastes for commuting, beyond the systematic variation with age, education, and children. Imagine, for example, people who travel to work by public transport: Some might at least enjoy to spend traveling time reading a book or newspaper, while others explicitly dislike crowded busses or trains. Similarly, some of the commuters who travel by car might be more fond of driving as such than others. A similar reasoning holds with respect to housing costs. In this particular case, including

[20]Official figures for Germany suggest that commuting patterns indeed vary substantially with age, gender, education, and income. See Statistisches Bundesamt (2005) for details.

[21]Though arbitrary, it seems realistic that the variation in tastes for wages is less pronounced than that in tastes for commuting time or housing cost.

$p_{n,a}$ in $Z_{n,a}$ amounts to assuming that individual tastes for housing costs vary even for households having the same income and the same demand for living space.[22] Analogously to commuting time, the coefficient on housing cost is assumed to be lognormally distributed and thus the negative of housing cost is used in estimation.

As outlined above, the empirical setting exhibits a nested structure as the choice of four alternatives is analyzed in three different labor market-regions. To take account of this structure, $Z_{n,a}$ includes indicator variables for each nest (i. e. for each labor market region), δ^k, which are assumed to have a normal distribution. As the random coefficients on the δ^k's enter only the utility of alternatives within the respective nest k, possible correlation within a labor-market region is captured and no correlation between alternatives of different nests is induced.[23]

An obvious issue with the adopted setting is that two respective alternatives are always somehow similar to each other as they share one feature. There are, for example, two alternatives involving commuting (MN, NM) and two alternatives that imply living in the metropolitan center (MM, MN). It is therefore not reasonable to expect tastes for these alternatives to be independent from each other a priori, an assumption that would hold in classic multinomial logit models and is known as independence of irrelevant alternatives (IIA). For this reason, indicator variables δ^a that identify the average taste for each alternative within each nest are included in $Z_{n,a}$, assuming that their coefficients are normally distributed in the population. The estimation of the parameters of the distributions of the coefficients β_n thereby explicitly allows for arbitrary correlation patterns between the variables contained in $Z_{n,a}$. Thus, any unobserved correlation over alternatives is captured by estimating the parameters of the distribution of the coefficients of the δ^a's. Moreover, this approach also takes care of possible differences in the variance of unobserved factors between alternatives, since the variance of tastes for each alternative is explicitly estimated. The assumption that the error terms $\varepsilon_{n,a}$ are homoscedastic and i. i. d. extreme value therefore remains

[22]However, one can think of arguments in favor of the hypothesis that tastes for housing costs are almost identically distributed for people with the same income and demand for space. Therefore, different specifications are presented, where the housing cost variable enters $X_{n,a}$ or $Z_{n,a}$, respectively.

[23]This approach is analogous to a nested logit model, which itself is a special case of the mixed logit model. See Train (2003) for a discussion.

valid.[24] Note, however, that the alternative specific constants also capture the average tastes for local characteristics of the alternatives, that have been labeled amenities in the theoretical model of the previous section.

To be precise, let β^δ be the vector of coefficients on all δ^a and δ^k, and let β^c be the vector of coefficients on commuting time and housing costs. Then, I assume that $\beta^\delta \sim N(b^\delta, \Omega)$ and that $ln(\beta^c) \sim N(b^c, \Omega)$ for general Ω. Hence, the exact parameters to be estimated are the means of the (natural logarithms of) coefficients b^δ (b^c), along with a lower triangular Choleski factor L of Ω, such that $LL' = \Omega$.

4 Results

This section reports the estimation results of several specifications of estimation equation (5), given equations (7), (8), and (9).[25]

4.1 Estimation

The results of the mixed logit model are reported in Table 2. The coefficients on the alternative specific constants within each nest, δ^a, as well as those on the labor-market region specific fixed effects, δ^k, are estimated together with their standard deviations in all specifications. It is assumed that they are correlated and follow a normal distribution with the reported means and standard deviations. In the specifications reported in columns 1 and 2 of Table 2 only the coefficient on commuting time is allowed to vary over decision makers, while wages and housing cost are modeled to be valued identically in the population. The estimations reported in columns 3 and 4 treat housing costs as an additional random coefficient. Furthermore, the specification reported in column 2 (column 4) is identical to that of column 1 (column 3) but includes some basic individual

[24] See Train (2003) for a discussion.

[25] All estimations, simulations and calculations are carried out using the mixlogit Stata command by Hole (2007), and my own Stata/Mata code. The code may be obtained from the author on request.

characteristics as fixed coefficients. The results and simulations reported in the following sections are all based on the estimation presented in column 3.

In general, the empirical model clearly confirms the predictions from economic theory as all coefficients show the expected signs and are precisely estimated. Higher wages attract people, while higher commuting time and higher housing costs make an alternative less likely to be chosen. Furthermore, the maximum simulated likelihood estimation procedure yields very robust results, as the coefficients on these variables are quantitatively comparable across the different specifications. The estimated standard deviations of the random parameters are highly significant in all cases, indicating that tastes for commuting time and housing costs indeed do vary in the population. Note, that this variation may be due to unobservable characteristics as well as to observable ones, which are not included in the model. However, the estimated standard deviations remain significantly different from zero after inclusion of some basic personal characteristics (columns 2 and 4). Thus, I find significant variation in tastes for commuting time and housing costs even for similar types of households.[26] The parameters on commuting time and housing cost reported in Table 2 are the means and standard deviations of $ln(\beta)$. The associated means and standard deviations of β are given in Table 3.[27] The standard deviations of the coefficients on commuting time and housing cost are relatively high compared to the coefficients themselves. Apparently, the degree of variation in tastes in the population is of considerable magnitude. This result is not really surprising as the individual cost per minute of commuting time is very likely to differ greatly, with observable characteristics like age or income, as well as with unobservable tastes for circumstances involved with commuting (e. g. driving a car or using means of public transport). One can easily think of similar arguments regarding the taste variation for housing costs.

In the main specification reported in column 3 of Table 2, the estimated means and standard deviations of the coefficients on the fixed effects for alternatives are all significantly different from zero. According to the estimates, there is substantial variation in tastes for combinations of working place and place of residence. In particular, the distribution of the valuation of the "typical"

[26]Remember that the housing cost variable already explicitly captures the housing cost for households of equal size and income.

[27]The mean of β is calculated as $exp(b+(s^2/2))$, its standard deviation is calculated as $exp(b+(s^2/2))*\sqrt{exp(s^2)-1}$, where b and s represent the estimated mean and standard deviation of the distribution of $ln(\beta)$.

Table 2: Results of the Mixed Logit Estimation

	1		2		3		4	
Variable	*Parameter*	*SE*	*Parameter*	*SE*	*Parameter*	*SE*	*Parameter*	*SE*
MM (mean of coefficient)	6.76***	(1.31)	4.74***	(.665)	3.05***	(.249)	3.58***	(.338)
MM (SD of coefficient)	4.99***	(.974)	5.93***	(1.01)	2.30***	(.337)	4.27***	(.565)
NN (mean of coefficient)	4.86***	(1.27)	3.32***	(.700)	.757***	(.271)	1.49***	(.372)
NN (SD of coefficient)	3.06***	(.837)	2.38***	(.432)	.986***	(.104)	.893***	(.177)
NM (mean of coefficient)	3.11**	(1.43)	-.498	(.789)	-1.61**	(.642)	-.723	(.469)
NM (SD of coefficient)	9.08***	(.911)	4.49***	(.726)	5.44***	(.632)	3.61***	(.497)
BERLIN (mean of coefficient)	.725***	(.071)	.530***	(.062)	1.14***	(.154)	.910***	(.201)
BERLIN (SD of coefficient)	.605**	(.242)	.698***	(.155)	1.95***	(.290)	1.70***	(.389)
MUNICH (mean of coefficient)	.551***	(.064)	.682***	(.049)	1.52***	(.145)	1.53***	(.179)
MUNICH (SD of coefficient)	.879***	(.178)	1.05***	(.176)	3.06***	(.340)	2.95***	(.415)
Commuting Time (mean of ln(coefficient))	-3.49***	(.130)	-6.61***	(1.26)	-4.24***	(.154)	-5.55***	(.344)
Commuting Time (SD of ln(coefficient))	1.07***	(.087)	1.97***	(.583)	1.68***	(.078)	2.16***	(.136)
Housing Cost (mean of ln(coefficient))^a	-.035***	(.001)	-.036***	(.002)	-3.35***	(.077)	-3.33***	(.122)
Housing Cost (SD of ln(coefficient))					1.47***	(.065)	1.57***	(.084)
Wage (coefficient)	.005***	(.001)	.003***	(.001)	.005***	(.002)	.003**	(.002)
Commute X Age (coefficient)			.073***	(.024)			.043***	(.015)
Commute X Children (coefficient)			.866***	(.213)			.611***	(.105)
Commute X Education (coefficient)			-.021	(.014)			-.008	(.010)
M X Age (coefficient)			-.198***	(.026)			-.147***	(.017)
M X Children (coefficient)			-1.52***	(.188)			-1.15***	(.117)
M X Education (coefficient)			.146***	(.020)			.114***	(.011)
SLL	-78475.92		-78151.53		-78341.89		-78002.29	

Dependent variable: Choice of alternative a, with $a = MM_k, MN_k, NN_k, NM_k$, and $k = Berlin, Hamburg, Munich$. Omitted categories of fixed effects are: $\delta^a = MN$, $\delta^k = Hamburg$. All reported standard deviations are calculated on the basis of the estimated Choleski factors L. ^{a}: Reported parameter corresponds to mean of ln(coefficient) in columns 3 and 4, and to coefficient in columns 1 and 2. *** denotes significance at 1% level (** at 5%, * at 10%). 442416 observations correspond to 36868 individuals. 100 Halton draws used for simulation.

Table 3: Lognormal Distributed Coefficients

	1	2	3	4
Commuting Time (mean of coefficient)	.054	.009	.060	.040
Commuting Time (SD of coefficient)	.079	.064	.240	.409
Housing Cost (mean of coefficient)			.103	.122
Housing Cost (SD of coefficient)			.284	.397

Columns 1, 2, 3, and 4 directly refer to columns 1, 2, 3, and 4 of Table 2.

commuting option to live in the nonmetropolitan area and work in the central city seems to be very dispersed. Its mean is even negative, which means that, on average, this alternative is disliked compared to the option to commute from the center to the nonmetropolitan area. More precisely, the estimated distribution of the coefficient implies that roughly 62% of households prefer the omitted alternative, while the other 38% prefer to commute from the suburbs to the center. This seems a little surprising but might be due to lower commuting time per distance in the direction from the center to the suburbs. In contrast, both non-commuting alternatives are on average preferred to the omitted alternative. The distributions of these coefficients imply that only around 9% (22%) of households place a negative value on the alternative to live and work in the metropolitan area (in the nonmetropolitan area) when compared to the alternative to commute from the center to the suburbs. With respect to the primary choice of labor-market region, both Berlin and Munich seem to be preferred to Hamburg on average. However, the distributions of these coefficients show considerable dispersion, too, with roughly one third of the population preferring Hamburg to both of the cities.

All reported standard deviations are calculated on the basis of the estimated Choleski factors L. The elements of the corresponding variance-covariance matrix Ω are almost all estimated significantly at at least the 5% level, indicating that there does exist sizeable correlation between the coefficients.[28] The implied correlation pattern is reported in Table 4. The correlation between $a = MM$, $a = NN$,

[28]In fact, only the covariance of $\delta^{a=MM}$ and housing cost and the covariance of $\delta^{a=NM}$ and $\delta^{a=NN}$ are insignificant. While the former result is not of much interest, the latter is surprising. It implies that there is no significant correlation between tastes for the two alternatives that both involve residing in the nonmetropolitan area.

Table 4: Correlation Matrix

	MM	NN	NM	B	M	Com	Hous
MM	1						
NN	.529	1					
NM	.420	*-.164*	1				
BERLIN	-.083	-.682	-.182	1			
MUNICH	-.376	-.830	-.187	.898	1		
Commuting Time	.099	-.626	.339	.663	.761	1	
Housing Cost	*-.059*	-.639	.303	.535	.741	.966	1

Calculations based on estimates reported in column 3 of Table 2. Figures in italics are statistically not significant.

and $a = NM$ is positive implying that households preferring the option to live and work in the center to the option of commuting from the center to the suburbs would also favor the two other alternatives. The correlation between housing cost and commuting time is positive and fairly large. Households with above average valuation of housing cost obviously also place higher than average values on commuting time. This is interesting as the high degree of correlation indicates that both types of cost are valued together compared to the other variables. Furthermore, the coefficients on the labor market fixed effects are strongly correlated. Again, this positive correlation is not surprising as these variables form a group relative to the other covariates.

The specifications reported in columns 2 and 4 of Table 2 further include individual characteristics as fixed coefficients. The estimates on the personal characteristics provide further interesting insights. Accordingly, older people are less likely to live in the metropolitan area, but are more likely to commute, while people with higher education clearly prefer city centers and tend to commute less. Households with children apparently have a higher probability to commute and to live in nonmetropolitan areas, even if the higher demand for living space is taken into account via the housing cost variable.

The quantitative implications of the model are based on the predictions it delivers. Given the characteristics of each alternative, the predicted individual probability of choosing alternative a_k is

$$P_{n,a_k}(\widehat{\theta}) = \int \frac{exp(V_{n,a_k})}{\sum_j exp(V_{n,j})} f(\beta|\widehat{\theta}) d(\beta). \tag{10}$$

Table 5 reports the observed (column 1) and the predicted number of households (column 2) choosing each of the twelve alternatives. The figures in column 2 represent the sums of the predicted individual probabilities of picking a particular alternative a_k:

$$\sum_n P_{n,a_k}(\widehat{\theta}). \tag{11}$$

The predictive power of the model is quite good as the predicted choice pattern very closely resembles the observed pattern. The appropriateness of the econometric model is further confirmed by very exact predictions of the distribution of individual commuting times, wages, and housing costs. This fact is further exploited in section 5, where the effects of policy measures are simulated.

4.2 Elasticities

The coefficients of the mixed logit model have no direct interpretation, so I calculate the corresponding comparative static elasticities. These figures measure the *ceteris paribus* impact of an alternative specific variable on the choice of this (or another) alternative. The resulting elasticities of changes in wages, housing costs, and commuting time within each labor market region are reported in Appendix B. As the focus of this analysis is not on the choice of the labor market region, only the elasticities of changes within one respective labor market region are reported.[29] Note, that in the employed mixed logit model the percentage change in the probability for one alternative given a percentage change in one characteristic of this alternative (or any other alternative) depends on the characteristics of all alternatives. Thus, elasticities are not symmetric as in simple logit models. To give an example of how to read Table A.4, consider a one percent increase in commuting time for a household that resides and works in the metropolitan area of Hamburg. This

[29]Nevertheless, the reported elasticities are calculated allowing each household to choose from all twelve alternatives. The full set of all comparative static elasticities for changes in one exogenous variable would give a matrix with $12 \times 12 = 144$ elements. Thus, the reported Tables in the appendix represent the 4×4 matrices on the "diagonal" of the corresponding full set-matrices.

lowers the probability of this alternative to be chosen by 0.321%. At the same time, the probability that the household chooses to live in the central city of Hamburg and to commute to the suburbs increases by 0.022%. Analogously, the probability to live and work in the suburbs increases by 0.059%, and the incentive to commute from the suburbs to the center increases by 0.044% due to the rise in commuting time in alternative $a = MM$. In contrast, a one percent increase in the commuting time for alternative $a = MN$ ($a = NN$, $a = NM$) increases the probability that a household chooses to reside and work in the metropolitan area of Hamburg by 0.002% (0.017%, 0.025%). Note, that the elasticities for commuting time are highest in Berlin, where both the city center and the nonmetropolitan area are more spread out than in the other two regions. In general, households residing in the nonmetropolitan areas are much more sensitive to changes in commuting time than their counterparts in the centers, since they already face longer commutes. The wage elasticities are relatively similar across labor market-regions. Apparently, wage increases for households that commute from the center to the periphery have the strongest impact. The elasticities with respect to housing cost are relatively low compared to those of commuting time and wages, with the exception of Munich. In particular, households residing in the central area of Munich react remarkably sensitive to changes in housing cost. This is most probably due to the very high level of the cost of housing in the Bavarian capital.

These comparative static elasticities are valid if one thinks of individual households. However, by construction, an increase in wages for alternative $a = MM$ implies an increase in wages for alternative $a = NM$, too. Therefore, more general patterns of the effects of changes in the exogenous variables are reported in section 5.

4.3 Consumer Surplus

Not only policy makers might be interested in how people value the effects of particular policy measures. A result readily offered by this kind of analysis is the estimated willingness to pay for changes in wages, commuting time, and housing cost. Given the coefficients β from column 3 of Table 2, the compensating variation for each individual household that is associated with a change in attributes of the alternatives is calculated following Train (1998) and Cherchi and Polak (2005):

$$CV_n = \int \frac{1}{\beta^w} \left(ln \left(\sum_{a_k} exp(V^{pre}_{n,a_k}) \right) - ln \left(\sum_{a_k} exp(V^{post}_{n,a_k}) \right) \right) f(\beta|\theta^{pre}) d(\beta), \tag{12}$$

where the coefficient on wages, β^w, represents the marginal utility of income[30], and *pre* (*post*) refers to the situation before (after) the change.

Accordingly, the average compensating variation in the population associated with a 10% increase in commuting time (housing cost, wages) amounts to € 37.06 (€ 14.34, € 10.97).[31] In other words, an amount of € 37.06 in terms of daily wage is necessary to compensate households for the extended daily one-way commute. This is more than double the willingness to pay to avoid a deterioration of housing cost relative to income of the same magnitude. Further case specific results on consumer surplus are reported in the following section, where the overall effects of particular policy measures are discussed.

5 Quantitative Implications

The estimated model allows to carry out counterfactual simulations of the effects of policy measures that affect the analyzed variables. Two showcase scenarios are assessed on the basis of the model reported in column 3 of Table 2.

Scenario 1 *("Pendlerpauschale") An existing tax deductible for long distance-commuters is cut by German authorities, leading to a decrease in wages of commuters between metropolitan and nonmetropolitan areas of 10%.*

[30] This specification suggests that the marginal utility of income is independent from income. Train (2003) points out that this assumption is innocuous if the changes in consumer surplus are small relative to income, which is arguably the case in the analysis at hand.

[31] The integral is solved by simulation using 100 Halton draws.

Table 5: Model Predictions I: Number of Households

				Scenario 1		Scenario 2	
		Observed	Predicted	Predicted	Change	Predicted	Change
Hamburg:	MM	5460	5577	5606	.511	5576	-.019
	MN	349	376	360	-4.06	376	-.028
	NN	1988	1955	1967	.643	1954	-.023
	NM	1922	1912	1885	-1.42	1912	-.008
Berlin:	MM	10848	10450	10495	.426	10450	.001
	MN	580	559	542	-3.00	560	.182
	NN	3003	2640	2655	.552	2644	.157
	NM	1685	1649	1629	-1.20	1649	.008
Munich:	MM	4416	4922	4947	.515	4921	-.029
	MN	936	1049	1007	-3.96	1049	-.042
	NN	3654	3747	3778	.833	3746	-.040
	NM	2027	2031	1995	-1.79	2031	-.013

Calculations based on estimates reported in column 3 of Table 2. Individual choice probabilities are simulated using 100 Halton draws.

This scenario is designed to resemble the planned cut in the so called "Pendlerpauschale" in Germany, which came into effect in 2007 and has been rescinded after being halted by the German Federal Constitutional Court (Bundesverfassungsgericht) in the end of 2008. This "Entfernungspauschale" is an income tax-deductible of € 0.30 per kilometer of (daily) commuting distance. Its roots date back as far as 1920. The described cut planned to grant the deductible only for commuting distances exceeding 20 kilometers instead of the entire distance. Columns 3 and 4 of Table 5 show the effects of this political measure on the spatial distribution of households in the three analyzed labor market-regions. Column 3 reports the predicted number of households that choose each option after the cut of the subsidy, calculated according to equation (11). The implied percentage change compared to the situation before the policy measure (as shown in column 2) is reported in column 4. Little surprisingly, the wage drop for the "commuting alternatives" leads to a decrease in households that choose these alternatives in each of the regions of Hamburg, Berlin, and Munich. In contrast, in each region the population that works and lives either in the center or in the suburbs rises after the subsidy cut. The alternative that experiences the largest relative drop in attractiveness is the option to commute from the center of Hamburg to its suburbs, where the number of choices decreases by 4.06%. The alternative that gains most appeal to households is to live and work in the nonmetropolitan area of Munich, with an increase of 0.83%. Note, however, that the subsidy also leads to changes in the choice of labor-market region. While Hamburg looses one inhabitant, 22 households choose alternatives in Berlin instead of Munich as a consequence of the subsidy cut. The reason for this pattern is that average wages and relative housing costs in Munich are above the sample average, while the housing cost in Berlin is far below average. Given this constellation, the uniform percentage decrease in wages of commuters draws households from the high cost alternatives in Munich to the low cost region of Berlin. Although interesting, the choice of the labor-market region itself is not the focus of this paper. Therefore, Table 6 reports the average predicted effects of scenarios 1 and 2 for the four intra-regional alternatives ($a = MM, MN, NN, NM$) only. The figures in Table 6 are the sums of the individual choice probabilities for the respective alternatives a, averaged over the three labor market-regions k:

$$\frac{1}{K}\sum_{k}^{I}\sum_{n}^{N}\overline{P}_{n,a_k}(\widehat{\theta}),$$

where the individual choice probabilities are now calculated under the implicit assumption that the choice of the labor-market region is irreversible:

$$\overline{P}_{n,a_k}(\widehat{\theta}) = \int \frac{exp(V_{n,a_k})}{\sum_j exp(V_{n,j_k})} f(\beta|\widehat{\theta})d(\beta).$$

As can be seen from Table 6, the average effects of the subsidy cut on the choice of the alternatives within regions does not differ much from that seen in Table 5. A look at the aggregated effects is a little more revealing, though. The political measure leads to a predicted increase in the population of metropolitan areas of 0.09%, while the population of nonmetropolitan areas drops by 0.14%. The total number of households that commute between centers and suburbs drops sharply by almost 2% in response to the subsidy cut.

Table 6: Model Predictions II: Number of Households

			Scenario 1		Scenario 2	
	Observed	Predicted	Predicted	Change	Predicted	Change
MM	20724	20432	20526	.464	20429	-.012
MN	1865	2119	2044	-3.53	2119	.017
NN	8645	8562	8623	.706	8565	.026
NM	5634	5755	5675	-1.40	5755	-.004
M	22589	22550	22570	.089	22548	-.009
N	14279	14318	14298	-.140	14320	.014
COM	7499	7874	7719	-1.97	7874	.002

Calculations based on estimates reported in column 3 of Table 2. Individual choice probabilities are simulated using 100 Halton draws.

The present model allows to estimate the willingness to pay for the subsidy cut in scenario 1. The individual household's compensating variation associated with the political measure is simulated according to equation (12), where 100 Halton draws are used to simulate the integral. The resulting average change in consumer surplus that is associated with the cut-back of the subsidy to commuters amounts to € 2.28.

Scenario 2 *(Minimum Wage) The German government introduces a uniform minimum wage of € 7.50.*

Scenario 2 simulates the location choices of households if all wages below a threshold of € 7.50 were lifted onto this level. In the presence of a wage premium in agglomerations, which is clearly indicated by the summary statistics of the present analysis,[32] this should lead to a stronger relative increase in average wages in the nonmetropolitan areas. Büttner and Ebertz (2009) point out that under decreasing marginal returns to labor in regional production, a uniform minimum wage leads to a shift of population from rural to agglomerated regions. However, the present simulations can

[32]See Lehmer and Möller (2007) and Büttner and Ebertz (2009) for quantitative evidence on the so called urban wage premium in Germany.

only focus on household decisions and do not account for the production side. Thus, the outcome will be different in that we expect the choice probabilities of alternatives that gain most through the introduction of the minimum wage to rise. The figures in columns 5 and 6 of Table 5 confirm this expectation, although the quantitative effects are fairly small. If households were free to choose from all options, the minimum wage of € 7.50 would draw decision makers from virtually all alternatives in Hamburg and Munich to all of the options in the region of Berlin. Especially the alternatives that involve working in the periphery of Berlin experience a strong rise in choice probability, with 0.18% for commuting from the center and 0.16% for living and working in the nonmetropolitan area. This is because wages in the East-German periphery of Berlin are well below the sample average and the percentage of incomes below the minimum wage of € 7.50 is by far highest there. In contrast, the largest population losses are induced for the alternatives to commute to the nonmetropolitan area of Munich, and to live and work in that area, respectively. This is exactly the peripheral region in the sample that exhibits the highest wages and the lowest incidence of the minimum wage. In total, the model predicts a population gain of 6 households for Berlin and losses of 2 households for Hamburg and 4 households for Munich, respectively. As the wage differences between nests are relatively large, the results in Table 6 provide much more insights regarding the effect of the minimum wage on the center–periphery system within a labor-market region. Given that the choice of labor-market region is fixed, the minimum wage of € 7.50 leads to an average reduction of households that choose to live and work in the metropolitan areas of 0.012%. The option to commute to the metropolitan area is chosen 0.004% less. The relative stronger growth of wages in the nonmetropolitan areas leads to an increase in the number of households that choose to work there: The number of choices in favor of living and working in the periphery (living in the metro area and working in the periphery) increases by 0.026% (0.017%). In total, we see a slight population gain for nonmetropolitan areas (0.014%), while metropolitan area population drops by 0.009%. Furthermore, the introduction of the minimum wage leads to an increase in the overall number of commuters of 0.002%.

As in the previous scenario, I use simulation techniques to estimate the individual willingness to pay for the introduction of the minimum wage according to equation (12). The average compensating variation associated with the introduction of a minimum wage of € 7.50 is € 0.10. Note, that this figure is positive since this simulation does not account for possible employment effects. In fact, the simulation assumes that wages at each alternative are independent of employment at that alternative.

While it is clear that the present model can only predict household behavior and has no power to consider any equilibrium effects determined through the interplay with the production sector, another important caveat has to be kept in mind regarding the simulated effects. Similarly, any adjustments on the housing markets provoked by shifts in the population are not incorporated in the model. The same is true for possible nonlinear congestion effects on commuting time.

6 Conclusion

This paper empirically quantifies the effects of wages, housing costs, and commuting time on the joint residential and job location choice of households. Applying discrete choice methods to a large set of micro-data allows a comprehensive empirical analysis of the three most important economic determinants of location choice. The analysis focuses on the household's decision to live and work either in the central metropolitan area, or the surrounding nonmetropolitan area, or to commute between the two. Objects of investigation are the regional labor markets constituted by the urban centers of the largest German cities Berlin, Hamburg, and Munich. A mixed logit approach is employed where coefficients are allowed to vary randomly over decision makers instead of being constant. This estimation strategy avoids the restrictive IIA assumption that is implicit in simple multinomial logit estimation. Moreover, arbitrary correlation patterns of coefficients are explicitly allowed for as correlation between tastes for the alternatives is very likely in the adopted choice setting.

The estimates fully confirm the important role of wages, housing costs, and commuting time for individual location choice, as predicted by economic theory. However, the results show that tastes for commuting time and housing costs do vary substantially within the population. Estimated elasticities show how changes in wages, housing costs, or commuting time affect the distribution of households between metropolitan and nonmetropolitan areas. Interestingly, there are no systematic differences in the magnitude of the impacts between the three factors. However, the effects of the economic determinants do vary over alternatives. To illustrate the quantitative implications of these results, two counterfactual scenarios are predicted. Accordingly, a general 10% cut in the wages of commuters would lead to an increase in urban population of 0.09% and a decrease in the population of nonmetropolitan areas of 0.14%. Total commuting decreases by almost 2%. Furthermore, the introduction of a uniform minimum wage of € 7.50 leads to a decrease (increase) of urban (rural) population of 0.009% (0.014%). In addition, both political measures result in minor shifts of the population between the three labor market-regions. The estimated overall willingness to pay to avoid the wage drop amounts to € 2.28, while the change in consumer surplus associated with the minimum wage of € 7.50 is € 0.10.

Economic theory also emphasizes the role of local amenities for the household's location choice. The present study captures such effects by alternative- and region specific fixed effects only. Any particular amenities are not explicitly addressed due to the excessive time cost and technical limits that are implied by the computational complexity of the applied estimation method. However, the estimation of willingness-to-pay figures for local amenities using appropriate, simulation based discrete choice methods remains a worthwhile aim for future research.

Acknowledgements

I am very grateful to Hannes Ullrich for helpful discussions and comments. I am indebted to Sabine Christ, Björn Milsch, and Hannes Ullrich for editorial help. I also thank Thiess Büttner for inspiration and useful comments.

Appendix A: Counties of the (Non)Metropolitan Areas

Labor-market region of Hamburg:

- Metropolitan Area: Urban county of Hamburg (Kreisfreie Stadt Hamburg).
- Nonmetropolitan Area: Counties (Landkreise) Harburg, Rotenburg (Wümme), Stade, Herzogtum Lauenburg, Pinneberg, Segeberg, Stormarn.

Labor-market region of Berlin:

- Metropolitan Area: Urban county of Berlin (Kreisfreie Stadt Berlin).
- Nonmetropolitan Area: Urban counties (kreisfreie Städte) Frankfurt a. d. Oder, Brandenburg a. d. Havel, Potsdam. Counties (Landkreise) Oberhavel, Barnim, Märkisch Oderland, Oder-Spree, Dahme-Spreewald, Havelland, Potsdam-Mittelmark, Teltow-Fläming.

Labor-market region of Munich:

- Metropolitan Area: Urban county of Munich (Kreisfreie Stadt München).
- Nonmetropolitan Area: Counties (Landkreise) Dachau, Ebersberg, Erding, Freising, Fürstenfeldbruck, Landsberg a. Lech, München, Starnberg.

Appendix B: Summary Statistics and Comparative Static Elasticities

Table A.1: Sample Means by Alternatives a: Berlin

Variable	$a = MM$	$a = MN$	$a = NN$	$a = NM$
Location specific				
Commuting Time	33.4	46.4	26.4	51.2
Housing Cost	7.97	7.42	3.32	3.04
Wage	90.1	75.2	72.1	87.6
Individual				
Age	40-44	40-44	40-44	40-44
(Age Category)	(7.07)	(6.48)	(6.70)	(6.85)
Children	.233	.262	.316	.360
Education	11.5	11.7	11.0	11.0
Observations	10848	580	3003	1685

Individual figures weighted by individual sampling probabilities.

Table A.2: Sample Means by Alternatives a: Hamburg

Variable	$a = MM$	$a = MN$	$a = NN$	$a = NM$
Location specific				
Commuting Time	28.2	36.8	21.3	46.5
Housing Cost	13.9	13.8	4.97	4.24
Wage	99.8	95.5	89.6	104
Individual				
Age	40-44	40-44	40-44	40-44
(Age Category)	(6.82)	(6.59)	(7.01)	(7.17)
Children	.188	.140	.349	.335
Education	11.5	11.4	10.5	10.9
Observations	5460	349	1988	1922

Individual figures weighted by individual sampling probabilities.

Table A.3: Sample Means by Alternatives a: Munich

Variable	$a = MM$	$a = MN$	$a = NN$	$a = NM$
Location specific				
Commuting Time	26.2	32.9	26.8	42.8
Housing Cost	34.0	38.2	15.2	12.3
Wage	108	102	99.0	107
Individual				
Age	40-44	40-44	35-39	40-44
(Age Category)	(6.54)	(6.51)	(6.34)	(6.79)
Children	.187	.162	.262	.233
Education	12.1	12.1	10.8	11.5
Observations	4416	936	3654	2027

Individual figures weighted by individual sampling probabilities.

Table A.4: Comparative Static Elasticities

	Commuting Time: Hamburg			
	MM	MN	NN	NM
MM	-.321	.002	.017	.025
MN	.022	-.261	.018	.011
NN	.059	.005	-.755	.024
NM	.044	.002	.012	-.821

	Commuting Time: Berlin			
	MM	MN	NN	NM
MM	-.705	.010	.145	.061
MN	.137	-.846	.068	.020
NN	.715	.024	-1.74	.074
NM	.262	.006	.064	-1.93

	Commuting Time: Munich			
	MM	MN	NN	NM
MM	-.509	.019	.071	.038
MN	.069	-.505	.141	.032
NN	.096	.049	-.756	.059
NM	.064	.014	.069	-1.46

	Housing Cost: Hamburg			
	MM	MN	NN	NM
MM	-.237	.002	.007	.005
MN	.033	-.243	.013	.004
NN	.054	.006	-.220	.006
NM	.043	.002	.006	-.148

	Housing Cost: Berlin			
	MM	MN	NN	NM
MM	-.205	.003	.020	.004
MN	.053	-.237	.015	.002
NN	.192	.007	-.225	.006
NM	.076	.002	.011	-.150

	Housing Cost: Munich			
	MM	MN	NN	NM
MM	-1.08	.035	.068	.019
MN	.177	-1.11	.188	.023
NN	.209	.106	-.651	.035
NM	.108	.025	.062	-.832

	Wage: Hamburg			
	MM	MN	NN	NM
MM	.326	-.006	-.041	-.022
MN	-.100	.505	-.106	-.019
NN	-.125	-.020	.383	-.014
NM	-.066	-.004	-.014	.309

	Wage: Berlin			
	MM	MN	NN	NM
MM	.245	-.004	-.022	-.011
MN	-.098	.411	-.042	-.007
NN	-.104	-.009	.306	-.006
NM	-.069	-.002	-.008	.371

	Wage: Munich			
	MM	MN	NN	NM
MM	.425	-.019	-.057	-.012
MN	-.090	.494	-.167	-.016
NN	-.075	-.045	.362	-.014
NM	-.032	-.009	-.025	.356

Calculations based on estimates reported in column 3 of Table 2. Individual elasticities are simulated using 100 Halton draws.

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