New Economic Geography and Regional Price Level

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Abstract. In New Economic Geography (NEG), price effects play a crucial role as a forward linkage in the cumulative process of spatial agglomeration. This paper examines the potential contribution of Helpman's NEG model in predicting cost of living and prices of goods groups at a regional scale. We particularly aim at developing NEG-based econometric models for the overall regional price level, prices of tradable and non-tradable goods and housing prices. The empirical price models are shaped with the aid of spatial-econometric techniques. The predictive power of alternative models is assessed by cross-validation using Southern German sample data.

Key words: Regional price level, Helpman model, spatial-econometric techniques, cross-validation

JEL: C21, R13, R31

1 Introduction

Although disparities in cost of living across space play a crucial role in regional economics and regional policy (Jüssen, 2005), knowledge on regional price levels is scarce in EU. National statistical offices do not gather price data area-wide. Collections of price data are usually carried out for constructing the consumer price index (CPI) at the national or state level. Although statistical offices of the states provide inflation rates for the sixteen NUTS-1 regions, the data do not allow for interstate price comparisons. In the United Kingdom, however, the private Reward Group regularly reports cost-of-living indices for the eleven standard (macro-)regions used *inter alia* in salary surveys (Johnston et al., 1996). Information on regional price levels at a lower regional level such as for NUTS-2 or NUT-3 regions is ordinarily not available.

On account of this lack of information, regional EU studies must usually rely on nominal indicators. Jüssen (2005) points to the necessity to "analyze convergence of real GDP in order to assess if regional policy is likely to achieve its objective of equalization". In measuring spatial disparities in standard of living, Aten and Heston (2005) estimate regional price levels using spatial-econometric models calibrated with national consumer price indices. The breakdown of country estimations to a regional level is, however, not easily justified. First, the econometric models built from international studies are primarily demand-orientated and not grounded in regional economic theory. Second, the calibration with national consumer price index does not necessarily imply an adequate explanation of regional price levels. Third, there is no *a priori* guarantee that responses of explanatory variables and spatial effects at the national and regional level are identical.

The present paper deals with developing regional price level models on the groundwork of New Economic Geography (NEG). Although the price index effect gives reason for the existence of forward linkages that operate towards agglomeration (Krugman, 1991; Fujta et al., 1999), NEG theory has been drawn only partially for regional price level determination (Brakman et al., 2004). We derive the basics of regional models for the consumer price index and its major components from Helpman's NEG model (Helpman, 1998). The empirical price models are shaped with the aid of spatial-econometric techniques. The predicitive power of the estimated price models is assessed by cross-validation.

Although regional CPI's are not regularly published in Germany, scattered surveys on regional price levels are conducted for selected cities at longer time spans. They potentially provide a basis for model calibration. The latest price comparison of selected cities from Germany as a whole took place in 1993 (Ströhl, 1994). Unfortunately, non-traded goods are only fragmentarily represented in consumer price indices (CPI) with this survey; while housing rents are completely disregarded. Price indices for all items as well as main goods groups are available for selected South German cities and towns for 2002 from a comparison of real purchasing power (BSMWVT, 2003). Particularly sub-price indices for tradables, non-tradables and housing are available from the Southern German sample. In this study, we use this sample data to calibrate and assess various NEG-based regional price models.

The subsequent sections of this paper are organized as follows. Section 2 discusses the predictions of the Helpman model on regional prices. In section 3, spatial-econometric models for the overall price level, the prices of tradable and non-tradable goods and housing prices are shaped. Section 4 explores spatial price effects, while NEG-based price level models are estimated and tested in section 5. In section 6, the empirical price models are cross-validated by means of the leave-one-out method. Section 7 concludes.

2 Regional price indices and Helpman model

Models of New Economic Geography (NEG) explain the development of agglomerations by means of increasing returns to scale, transportation costs and factor mobility. The Krugman model represents a prototype that consists of a two sectoral core-periphery structure (Krugman, 1991; Fujita et al., 1999, Ch. 4). In the modern sector varieties of a differentiated good are produced with increasing returns to scale by mobile workers across regions. The manufacturing sector is characterized by monopolistic competition. Industrial goods are traded across regions with transport costs increasing with distance.[1] Goods produced in the traditional sector are homogenous and termed "agricultures". The traditional sector operates with constant returns to scale under perfect competition. For agricultures no transport costs are incurred. Workers in the traditional sector are viewed to be immobile.

Forward linkages between firms and consumers act as centripetal forces that are strongly based on the price index effect (Robert-Nicoud, 2005). When firms move from one region to another, consumers will find a larger range of manufactured goods in the destination region. Because of their preferences for variety, they will benefit from the enlarging number of firms at their place of residence by saving transport costs. As each firm produces only one single variety in equilibrium, consumers' expenditures are spread over a larger number of differentiated goods. As a result, the price index of tradable goods (P_T) will decrease in regions with an increasing number of firms. This effect can be seen from the representation

$$P_{T,r} = \left[\sum_{s=1}^{n} N_s \left(p_s^M \cdot T_{sr} \right)^{1-\sigma} \right]^{1/(1-\sigma)}, \text{ r=1,2,...,n,} \tag{1}$$

of the price index for tradables in region r. p_s^M is the uniform price of manufactures in region s, N_s the number of varieties (= number of manufacturing firms) produced in region s and T_{sr} (T_{sr}>1) the transport costs incurred by shipping a variety from s to r. The parameter σ denotes the elasticity of substitution between any two varieties.[2] As all prices of manufactures are equal in equilibrium, the price of a variety produced by a firm that moves from s to r drops from $p_r^M T_{rs}$ to p_r^M. By virtue of the price index effect core-periphery models of Krugman-type predict a lower price level of industrial goods in agglomerations compared to peripheral areas (Krugman, 1991; Fujita et al., 1999, Ch. 4; Fujita and Thisse, 2002, Ch. 9).

The price of the non-traded good ("agriculture"), P_{NT}, is fixed and identical in all regions. Thus, the overall price index of Cobb-Douglas type,

$$P_r = P_{T,r}^{\mu} \cdot P_{NT,r}^{1-\mu}, \tag{2}$$

with μ as the share of expenditures spent on manufactures, does not cover any centrifugal forces. Potential centrifugal forces that might arise from congestion or housing costs are completely removed. Retaining the structure of the modern industrial sector, Helpman (1998) introduces a dispersion force into Krugman's core-periphery model by replacing the agricultural good with housing. As stock of housing,

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[1] In NEG models, transport costs are typically modelled by an "iceberg technology". Only a fraction τ of a variety shipped arrives at the destination. The part $1-\tau$ that "melts" away increases with distance.

[2] By virtue of normalization, σ also represents the price elasticity of demand of varieties.

H_r, is fixed in all regions, prices for housing tend to be high in densely populated centres and low in sparsely populated areas. In equilibrium, housing income and housing expenditures must be equalized:

$$P_{NT,r} \cdot H_r = (1-\mu)Y_r \,. \tag{3}$$

When income Y_r rises with immigration of firms and workers, housing rents $P_{NT,r}$ will increase if housing stock H_r is constant:

$$P_{NT,r} = (1-\mu)Y_r \cdot H_r^{-1} \,. \tag{4}$$

Thus, overall regional price level depends on the relative strength of centrifugal and centripetal forces. While transport costs act as an agglomeration force, housing costs operate towards dispersion.

The equilibrium relation for the price index of tradables reads

$$P_{T,r} = \left[\sum_{s=1}^{n} \lambda_s \cdot \left(w_s \cdot T_{sr}\right)^{1-\sigma} \right]^{1/(1-\sigma)} , \tag{5}$$

where λ_S is the share of region's share of total manufacturing labour force. Transport costs T_{sr} incurred by shipping a unit of manufactures from s to r are measured as a function of distance d_{sr} between s and r:

$$T_{sr} = T\left(d_{sr}\right), \;\; f\left(d_{sr}\right) > 0 \,. \tag{6}$$

Using the equilibrium condition that real wages are equalized across regions,

$$\frac{\omega_r}{P_{T,r}^{\mu} \cdot P_{NT,r}^{1-\mu}} = \frac{\omega_s}{P_{T,s}^{\mu} \cdot P_{NT,s}^{1-\mu}} \text{ for all } r \neq s, \tag{7}$$

the price index for tradable goods of region r, $P_{T,r}$, can be restated in terms of the fundamental economic variables Y_r, H_r and nominal wage ω_r:

$$P_{T,r} = \gamma \cdot Y_r^{\mu-1} \cdot H_r^{(1-\mu)/\mu} \cdot \omega_r^{1/\mu} \,. \tag{8}$$

In (8) γ is a constant. Let h_r be each individual's share in total housing income and L the labour force. Then region r's total income amounts to

$$Y_r = \lambda_r \cdot L \cdot (\omega_r + h_r) \,. \tag{9}$$

Because of housing is equally owned by individuals, h_r is a constant (Roos, 2001). Thus it may be advantageous to solve equation for w_r, in order to eliminate wage in the representation (8) of $P_{T,r}$. If we neglect the share of housing income, h_r, for simplification[3], the price index of tradable goods takes the form

$$P_{T,r} = \phi \cdot Y_r \;\cdot H_r^{(1-\mu)/\mu} \tag{10}$$

with ϕ as a constant.

Equations (4) and (10) can be viewed as the major components of NEG-based econometric models for compound prices for tradable and non-tradable goods,

[3] Cf. Brakman et al. (2004) who define income from the start only in terms of wages.

respectively.[4] Income asserts a positive influence on both sub-price indices, whereas the effect of housing stock is different. While an increasing housing stock entails a fall in housing rents, it is at the same time accompanied by a rise of prices of manufactures. If we combine both price equations (4) and (10) according to the Cobb-Douglas type overall price index (2), the housing variable would cancel out. Higher cost of living due to scarcity of housing stock is completely offset by a fall in prices of manufactures. Housing costs are not such a substantial centrifugal force to be able to outweigh opposite concentration forces. This potential weakness of the Helpman model can be tested in the space of a regional price level model.

3 NEG-based spatial-econometric price models

The price index for tradable goods (10) in the Helpman model is shown to be a non-linear function of income and housing stock. Nonlinearity is as well present in the determination of prices for housing (4) by virtue of the interaction of income and housing stock. Both equations can, however, be linearized by taking the logarithms on both sides. Summarizing the effects of all ignored influences by error terms ν and η we obtain the log-linear models

$$\ln P_{T,r} = \ln\phi + \ln Y_r + \frac{1-\mu}{\mu}\cdot\ln H_r + \nu_r \tag{10'}$$

and

$$\ln P_{NT,r} = \ln(1-\mu) + \ln Y_r - \ln H_r + \eta_r \tag{4'}$$

for sub-price indices of tradables and non-tradables. The models (10') and (4') represent the core of NEG-based econometric regional price level models. Additional variables may enter the model as control variables. In international price comparisons, it is particular controlled for geography, while income, openness and human capital are used as economic influence variables in a largely ad hoc manner (Aten and Heston, 2005).

According to equation (2) consumer price index P is determined by all model variables affecting P_T and P_{NT}. Let α_0 be the intercept, β_j the regression coefficients of the NEG-variables and γ_k the regression coefficients of the control variables X_k. Then the NEG-based econometric model for the consumer price level is of the form

$$\ln P_r = \alpha_r + \beta_1\cdot\ln Y_r + \beta_2\cdot\ln H_r + \sum_{k=1}^{m}\gamma_k\cdot X_{kr} + \varepsilon_r \tag{11}$$

with ε as the error term. The Helpman model imposes the following parameter restrictions:

for ln $P_{T,r}$: $\beta_1 > 0$, $\beta_2 > 0$, (12)

for ln $P_{NT,r}$: $\beta_1 > 0$, $\beta_2 < 0$, (13)

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[4] The basic idea of combining of some equilibrium relationships in order to obtain testable "price equations" resembles Hanson’s derivation (Hanson, 2005) of a NEG-based market potential function in form of the so-called wage equation for empirical testing purposes (see e.g. Mion, 2003; Niebuhr, 2004; Brakman et al., 2004).

for ln P_r: $\beta_1 > 0$, $\beta_2 = 0$. (14)

Instead of using individual geographic variables like climate, height, precipitation, water access, we capture spatial heterogeneity by latitude and longitude. They exert direct effects on regional prices, but as well capture influence of individual geographic variables not explicitly considered (Aten and Heston, 2005).

If spatial effects are ignored, the disturbances ε_r will not be an independently identically distributed random variable. They can manifest in form of spatial heterogeneity and/or spatial dependence (Anselin, 1988b, pp. 8; LeSage, 1999, pp. 3). The former type of spatial effect is strongly linked to nonstationarities of price level itself or in its relationship to other variables across space. Spatial autocorrelation refers to the fact that near phenomena are often more strongly related than distant matters of fact. Significance tests may become invalid and parameter estimates biased if spatial effects are ignored.

Spatial heterogeneity of regional prices may be present in form of south-north and/or west-east price gradients. In this case it can be captured by a trend surface model which consists of a polynomial equation in the coordinates x_r and y_r of a representative point in region r (Anselin, 1992). Rural districts are usually represented by the latitude and longitude coordinates of the district town. When the district town is itself an urban district, it is replaced by the next largest city in the district. The polynomial trend surface is easily be integrated into the price level model (11).

Substantive spatial price dependence can be accounted for by introducing the spatial price lag

$$W\_\ln P_r = \sum_{s=1}^{n} w_{rs} \cdot \ln P_s \,, \tag{15}$$

into the non-spatial model (11):

$$\ln P_r = \alpha_r + \rho \cdot W\_\ln P_r + \beta_1 \cdot \ln Y_r + \beta_2 \cdot \ln H_r + \sum_{k=1}^{m} \gamma_k \cdot X_{kr} + \varepsilon_r \,. \tag{16}$$

Equation (16) is known as the mixed regressive spatial autoregressive model (Anselin, 1988a, pp 34; LeSage, 1999, pp. 45). As we work with a sample of non-contiguous counties and cities, we define the spatial weights w_{rs} in terms of distances (Anselin, 1988a, pp. 17). The spatial autoregressive parameter ρ reflects the impact of the distance-weighted price level in nearby regions on region r's price level. The spatial lag model is particularly applied to capture price dependence arising from interregional trade (Keller and Shiue, 2004).

Price spillovers may, however, also explained by spatially lagged explanatory variables (Anselin, 2003). In his case, a spatial cross-regressive is formed by replacing the spatial price lag (15) by the spatially lagged income and housing stock

$W\_\ln Y_r = \sum_{s=1}^{n} w_{rs} \cdot \ln Y_s$ and $W\_\ln H_r = \sum_{s=1}^{n} w_{rs} \cdot \ln H_s$:

$$\ln P_r = \alpha_r + \beta_1 \cdot \ln Y_r + \rho_1 \cdot W\_\ln Y_r + \beta_2 \cdot \ln H_r + \rho_2 \cdot W\_\ln H_r + \sum_{k=1}^{m} \gamma_k \cdot X_{kr} + \varepsilon_r \,. \tag{17}$$

The model (17) may alternatively be used with distance-weighted income

$$\ln \widetilde{Y}_r = \ln Y_r + \sum_{s=1}^{n} w_{rs} \cdot Y_s \tag{18}$$

that is closely related to the concept of market potential as an important measure of market access (see e.g. Hanson, 2005).

Geographically distance-based weights rely on the hypothesis that spatial interaction between two regions r and s decreases with greater remoteness.[5] This may be attributed to increasing costs of moving people and goods between areal units. Cliff and Ord (1981, pp. 17) suggest a general spatial weights resting on both distance and common border length (Cliff and Ord, 1981, pp. 17). Usually, however, common border length is viewed as circumstantial with regard to spatial interaction. Thus, the Cliff-Ord weight weights reduce to the Pareto form[6]

$$w_{rs}^{*} = 1/d_{rs}^{-b}\text{, b > 0.} \tag{19}$$

The entries w_{rs}^{*} are termed unstandardized spatial weights. The distance decay parameter b controls the degree of downweighting of prices from spatial units with increasing distance to region r. The larger b, the less important are goods prices in far remote areas for region r's own price level. Simple inverse distance weights are given by a distance decay parameter of 1. The gravity model, however, causes the parameter b to be set equal to 2 (see e.g. Zhang and Kristensen, 1995; Bang, 2005). Inverse quadratic distance weights have proved better at adjusting for impedances like traffic congestion and topological barriers that tend to occur more frequently with growing distance (Gimpel et al., 2003).

A row-standardization of the original spatial weight matrix **W*** = $[w_{rs}^{*}]$, $w_{rs} = w_{rs}^{*} / \sum_{s=1}^{n} w_{rs}^{*}$, is preferable for a better interpretation (see e.g. Beck et al., 2004). For the row-standardized weight matrix **W** = $[w_{rs}]$, the range of parameter space is no longer dependent on the scale of the distance (Morenoff et al., 2001). Moreover, the spatial lags are measured in the same units as the attribute variable.

If nuisance causes spatially autocorrelated errors, we will employ the price level model (11) with a spatially autocorrelated error process

$$\varepsilon_r = \sum_{s=1}^{n} \lambda \cdot w_{rs} \cdot \varepsilon_s + \nu_r , \tag{20}$$

where ν is an independently identically distributed random variable. In case of normally distributed disturbances, consistent and efficient estimators of the regression coefficients are obtained by the method of maximum likelihood (Anselin, 1992).

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5 For a generalization of the geographical distance concept to the notion of an economic distance see e.g. Conley and Ligon (2002). Economic distances between spatial units could be defined by, for instance, trade flows or transport costs.

6 The diagonal elements w_{rr}^{*} are set equal to 0.

4 Exploratory Spatial Data Analysis

Regional price level models are estimated and tested for a Southern German sample of districts. The data on

- the consumer price index,

  and three sub-price indices of

- tradable goods, non-tradable goods and housing

are available from a comparison of real purchasing power in 2002 across 21 Bavarian municipalities.[7] The municipalities are divided in three size groups (see Appendix Table A1). While G and K communities are urban districts (*kreisfreie Städte*), A communities belong to rural districts (*Landkreise*). Because of data availability and comparability with regard to explanatory variables, we relate our data analysis on NUTS-3 regions, which means that price indices of A municipalities are considered as representative for the price level in the corresponding rural district. The number of price representatives the consumer price index is based on rises with the size group. Summary statistics of the consumer price index (CPI), various sub-price indices and explanatory variables are provided in Table 1.

Table 1: Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Consumer price index[a]	76.6	6.9	67.6	100.0
Price index of tradables[a]	82.2	5.6	72.6	100.0
Price index of non-tradables[a]	72.2	8.6	62.1	100.0
Housing price index[a]	67.6	10.3	54.0	100.0
Disposable Income[b]	3.149	5.428	0.715	26.179
Housing stock[c]	0.208	0.068	0.103	0.380
Human capital[c]	0.083	0.041	0.031	0.181
Longitude[d]	11.388	1.096	9.578	13.483
Latitude[d]	49.049	0.802	47.550	50.317

Sources
a BSMWVT (2003), b National Accounts of the States (*Volkswirtschaftliche Gesamtrechnung der Länder*), Statistical State Office Baden Württemberg, c Residential buildings per capita, Statistik regional (CD), Federal Statistical Office Germany, d Proportion of employees with a university degree/degree at an advanced technical college, Statistik regional (CD), Federal Statistical Office Germany, e information portal Informationsarchiv.com URL: http://www.informationsarchiv.com/regionalseiten/

Some information on spatial price dependence and local nonstationarity of the price indices across Southern German regions may point to the relevance of spatial effects in model building. Global spatial price autocorrelation is explored using Moran's I. Figure 1 displays the Moran coefficients for the range [1; 2] of the decay parameter b

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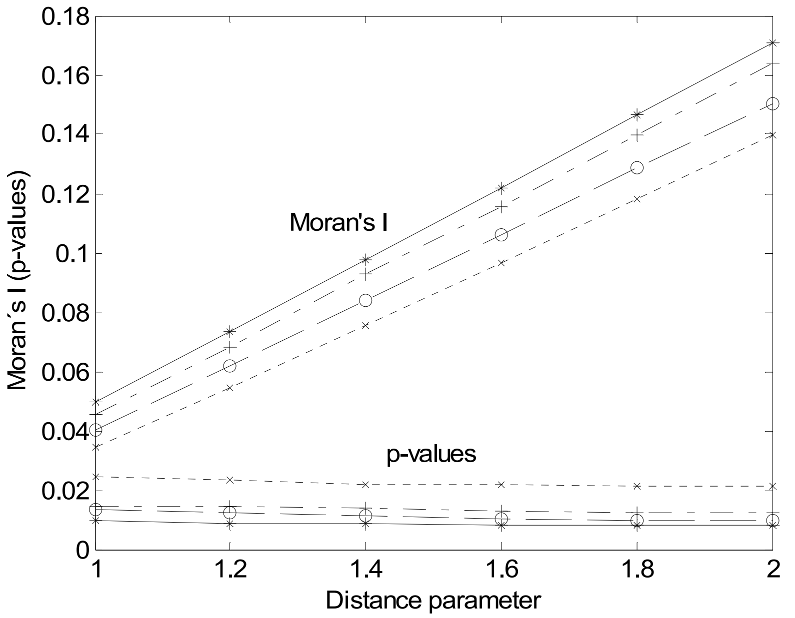
[7] BSMWVT (2003). The comparison is an updating of a study of the GFK Group, Nuremberg, on behalf of the Bavarian Ministry of Economic Affairs, Transport and Technology.

of Equation (19) along with the empirical significance levels (p-values) for the consumer price index (P) and for the three sub-price indices for tradables (P_T), non-tradables (P_{NT}) and housing (P_H). For all four indices Moran's I grows virtually linearly with larger distance decay. The Moran coefficient of the overall price level rises from 0.05 with inverse distance weights to 0.17 with inverse quadratic distance weights. Spatial autocorrelation is somewhat lower pronounced for the sub-price indices. This particularly holds for P_T and P_{NT}, where I rises from 0.04 (b = 1) to 0.13 (b = 2) and 0.034 (b = 1) to 0.10 (b = 2), respectively. Despite the varying strength of spatial association, the p-values show only a relative small decrease over the range $1 \leq b \leq 2$. For all parameter values b, the Moran coefficients are highly significant ($p < 0.01$) for P and P_M and significant ($p < 0.05$) for P_T and P_{NT}.[8] Thus, price levels do not appear to vary purely randomly across Southern German regions. Areas with a relatively high (low) price level tend to be located near areas with price levels above average more than by chance. According to the Moran tests, spatial dependence of regional price indices in Bavaria can be inferred from a broad range of distance-based spatial weight matrices.

Figure 1: Global Moran tests for regional price indices



Notes: *: Consumer price index, o: Price index of tradables, x: Price index of non-tradables, +: Price index of housing
Moran test [E(I) = -0.05]: Permutation approach: 10000 permutations

An increase of global Moran's I with growing distance decay can certainly be expected as more weight is given to nearby regions. For country income, Aten and Heston (2003) established a rise of Moran's I from 0.35 to 0.73 with replacing inverse distance weights by inverse squared distance weights. Although not compulsory, the

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[8] Significance tests are based on the permutation approach (Anselin, 1995). For large n Moran's I is asymptotically normally distributed (Cliff and Ord, 1981). Because of the medium-sized sample Southern German sample (n=21), the normal approximation would be doubtful.

latter specification is more "natural" when the gravity model is adopted (Isard et al., 1998, pp. 243; Sen and Smith, 1995). Moreover, in a comparative study Aten and Heston (2003) have shown that the quadratic distance specification matches much better with the contiguity approach over a broad band of distances. Using contiguity matrices with neighbouring regions lying inside a circle of radius of 100 up to 1000 miles, the Moran coefficient decreases from 0.89 to 0.74. This supports the view of Gimpel and Schuknecht (2003) that the squared distance function seems to capture the occurrence of impedance more realistically than the simple inverse distance function. In the following, we therefore confine spatial analysis to the use of a squared distance-based spatial weight matrix.

Although most areas are in line with the global tendency of positive spatial autocorrelation, a number of regions deviate from that pattern with each of the four price indices. They form pockets of nonstationarity as their own and surrounding price level depart from one another. Such pockets of instationarity are particular the regions of Nuremberg, Würzburg, Bamberg and Neuburg-Schrobenhausen, each of which lying at least twice in the group of areas with the three most negative I_r's (see Table 2). Other Bavarian cities share the positive spatial association with the bulk of the data, but to a much greater extent. The positive local autocorrelation of price level is for the city of Rosenheim so strongly pronounced that it clearly turns out to be an outlier according to the two-sigma rule.[9] The Bavarian capital of Munich, which appears for all price indices in the group of regions with the three largest positive I_r's, proves to be an outlier with respect to P_T. Both cities along with that of Bad Reichenhall render the largest contribution to global spatial price autocorrelation across Bavarian regions.

Table 2: Local Moran coefficients for regional price indices

Local Moran coefficients	Consumer price index (P)	Price index of tradables (P_T)	Price index of non-tradables (P_{NT})	Price index of housing (P_H)
# of positive I_r's	17	16	15	16
Largest positive I_r	I_{RO} = 1.239 (O)	I_{RO} = 0.982 (O)	I_{RO} = 1.172 (O)	I_{RO} = 1.354 (O)
	I_{MU} = 0.707	I_{MU} = 0.919 (O)	I_{BR} = 0.734	I_{BR} = 0.824
	I_{BR} = 0.683	I_{AU} = 0.138	I_{MU} = 0.483	I_{MU} = 0.719
# of negative I_r's	4	5	6	5
Most negative I_r	I_{NU} = -0.226	I_{RE} = -0.134	I_{NU} = -0.362	I_{NU} = -0.296
	I_{WU} = -0.162	I_{BA} = -0.112	I_{WU} = -0.200	I_{WU} = 0.227
	I_{NS} = -0.063	I_{NS} = -0.109	I_{19} = -0.035	I_{BA} = -0.074

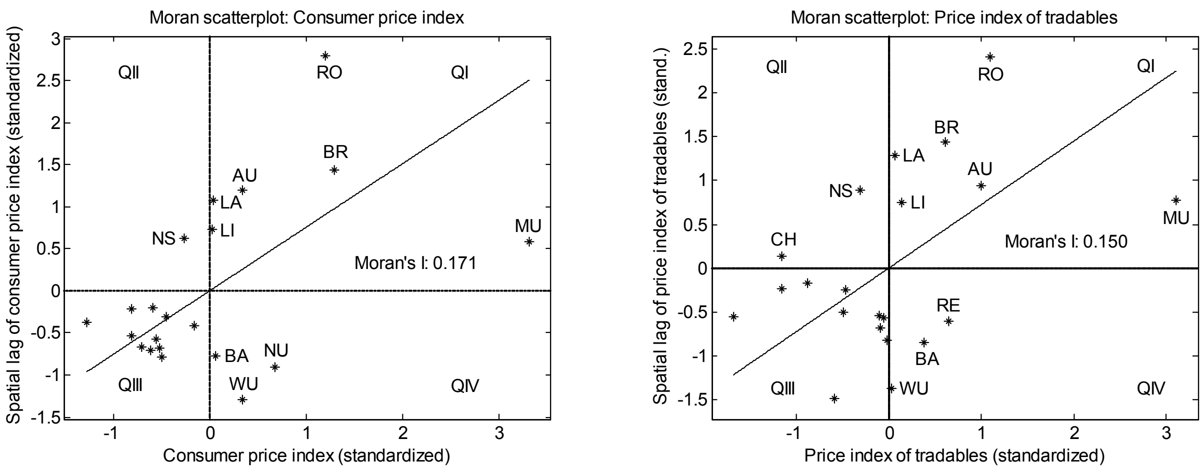
Notes: MU: Munich, BR: Bad Reichenhall, RO: Rosenheim, NU: Nuremberg, AU: Augsburg, WU: Würzburg, BA: Bamberg, RE: Regensburg, NS: Neuburg-Schrobenhausen, SF: Schweinfurt
O: Outlier according to the two-sigma rule

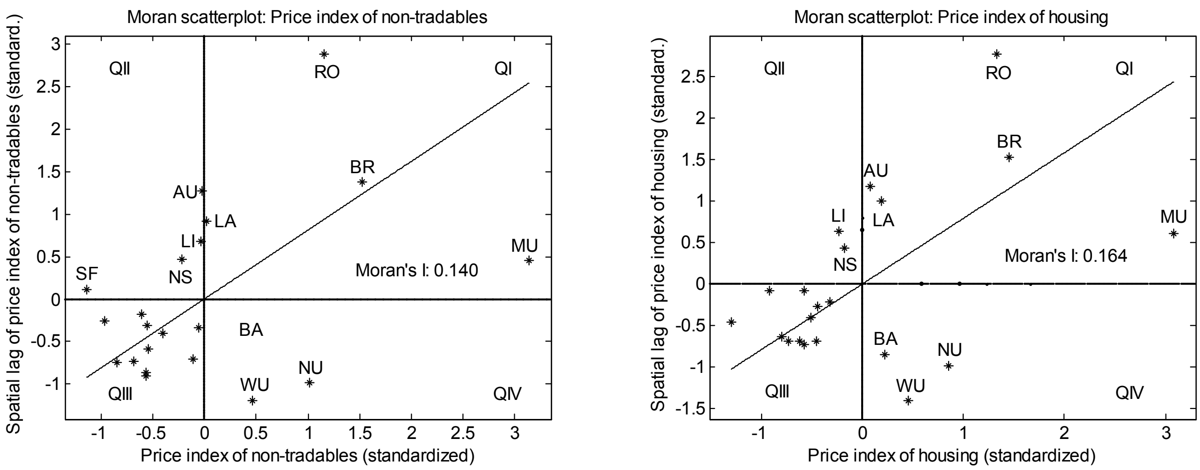
9 Note that the local Moran coefficients are not bounded to the interval [-1; 1].

More insight into the type of local spatial price dependence can be obtained with the aid of Moran scatterplots (Figure 2). In accordance with the local Moran coefficients, most regions are located in quadrants I and III where areal units with positive local spatial autocorrelation are located. The three cities with the three largest I_r's, Rosenheim, Munich and Bad Reichenhall, lie in quadrant I, which is characterized by regions with their own and surrounding high price level. Although its normed residual is not conspicuous, Munich proves to be a high leverage and influential data point for all price indices. Munich's Cooks's distance (CD) exceeds thrice the threshold of one. In contrast to Munich, Rosenheim is already identified to be an outlier by its residual values. Even though it is not a high leverage point, Rosenheim marks an influential data point as its CD value exceeds that of the next ranked region by factors between 3 ½ and 6 ½.

While observations in quadrant I consist of medium-sized and larger cities, most data points of quadrant III represent rural areas characterized by the lowness of their own and surrounding price level. Particularly the city of Regensburg, however, departs from this classification. The cities of Nuremberg, Würzburg and Bamberg turn out to form pockets of instationarity with their own high price level but surrounded by regions with low price levels (quadrant IV). Areas of spatial instationarity are also represented by the districts of Neuburg-Schrobenhausen, Cham and Lindau, with an unexpectedly low price level of their own, while that of nearby regions is above average (quadrant II).

Figure 2: Moran scatterplots of price indices





Notes:
MU: Munich, BR: Bad Reichenhall, RO: Rosenheim, NU: Nuremberg, AU: Augsburg, WU: Würzburg, BA: Bamberg, RE: Regensburg, NS: Neuburg-Schrobenhausen, SF: Schweinfurt, LA: Landau, LI: Lindau, CH: Cham

5 Estimating and testing NEG-based price models

Exploratory spatial data analysis has highlighted both spatial dependence and spatial heterogeneity of price levels across Southern German regions. Thus, we have to account for spatial effects in explaining regional (sub-)price indices of South German districts by NEG-based price level models. For all price indices, model specification and estimation is accomplished in two steps:

1st step

We only allow for spatial heterogeneity by adopting a trend surface and/or spatial expansion model. By means of Lagrange multiplier (LM) tests for spatial dependence we will establish whether spatial autocorrelation is still present in a price level model after accounting for spatial heterogeneity. In case of rejection of the null of independence, the kind of spatial dependence, spatial error or lag dependence, is exposed by the LM statistics.[10]

2nd step

In case of spatial error dependence, the final model is straightforward. When spatial dependence turns out to be substantive, however, we examine whether the effect of prices in nearby regions can be explained by spatially lagged explanatory variables. If this is the case, spatial price dependence is captured by a spatial cross-regressive model.

Although housing stock formally cancels out when combining the sub-price indices of tradables and non-tradables according to the Cobb-Douglas form (2), we use both

[10] See Anselin and Florax (1995). In OLS regressions we draw inferences on robust LM spatial lag and error tests because of their higher power to discriminate between both kinds of spatial dependence (Bera/Yoon, 1993; Anselin et al., 1996). With spatial lag or spatial error models only non-robust Lagrange multiplier (LM) or Likelihood ration (LR) tests for spatial dependence are available (see Anselin, 1988a, pp.65 and pp. 103).

explanatory variables in the spatial model of the consumer price index. This allows us to test the relevance of a centrifugal force in overall price level determination. The price effects of both variables are measured after controlling for human capital and geography.

As to geography, all regressions point to purely random effects of longitude, while latitude always appears to be significant. This finding is in line with that of international studies, where latitude is interpreted as a proxy for a broad set of geographic variables (Aten, 2001; Aten and Heston, 2005). For Western Germany a declining north-south gradient is well-known with regard to unemployment, while a decrescent south-north trend holds for income

Table 3: Spatial models for consumer price index

	Spatial models for the consumer price index (CPI)					
	Model 1		Model 2		Model 3	
	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value
Constant	6.363	9.089	3.725	2.292	5.984	10.695
Spatial price lag			0.463	1.739		
Income	0.039	2.429	0.041	3.622	0.038	2.872
Housing stock	-0.080	-3.130	-0.070	-2.033	-0.070	-2.958
Spatial stock lag					-0.246	-2.587
Human capital	0.036	1.470	0.040	1.802	0.045	1.862
Latitude	-0.043	-2.847	-0.029	-2.188	-0.042	-3.308
R^2	0.761		0.770		0.825	
SER	0.0472		0.0389		0.0417	
L*	37.199		38.023		40.473	
AIC	-64.399		-64.046		-68.947	
JB	0.183 (0.913)				0.821 (0.663)	
BP	6.107 (0.191)		6.128 (0.190)		8.488 (0.131)	
LM(lag) / LR(lag)	5.521 (0.019)		1.648 (0.199)		0.046 (0.830)	
LM(error)	4.273 (0.039)		2.435 (0.119)		0.131 (0.718)	

Notes:
R^2: Coefficient of determination, SER: Standard error of regression, L*: Log likelihood, AIC: Akaike information criterion, JB: Jarque-Bera test, BP: Breusch-Pagan LM test for heteroscedasticity, LM(lag): Robust LM spatial lag test, LR(lag): Likelihood ratio test for spatial lag model, LM(error): Robust LM spatial error test

per capital and employment. In the space of Bavaria, northern administrative districts of Upper Palatinate and Upper Franconia are known to experience noticeably higher unemployment than areas in Upper Bavaria. Thus, a clear-cut south-north price gradient seems to reflect differences in economic performance.

No evidence for a substantial interaction effect between income and latitude on the overall price level is revealed. This suggests that spatial heterogeneity in consumer price index will be captured by a trend surface. Table 3 exhibits the estimates of the extended trend surface model for the consumer price index. About 76 per cent of regional variation in the overall price level can be explained by the above discussed economic factors along with a north-south trend. As expected, regional price level rises with growing income, while dwelling capacity and latitude act in the opposite direction. Human capital exerts at best a weak positive influence on regional prices. When ignoring spatial dependence, the significance of that explanatory variable fails to be proved. As both robust LM statistics for spatial dependence are significant, but the empirical significance level with LM(lag) is lower than that of LM(error), we have most notably been concerned with spatial lag dependence (Anselin, 1992; Anselin et al., 1996).

There is no evidence for heteroscedasticity and non-normal distributed errors. Diagnostics point to substantive spatial dependence rather than to spatial error dependence for the CPI. Although the spatial lag model improves the model performance, it does not provide the best fit. Table 3 (model 3) shows that spatial price lag can be well explained by spatially lagged dwelling capacity. After accounting for a spatial capacity lag, both LM statistics turn out to be nonsignificant. All criteria identify the spatial cross-regressive model as superior.

As the impact of housing stock on overall price level is expected vanish, its significant negative effect points to some weakness of implementing the non-tradable goods sector in Helpman's NEG model. Scarcity of housing stock in centres may increase overall cost of living thereby potentially establishing a strong centrifugal force. This effect seems to be enforced by dwelling capacity in surrounding regions.

In the spatial models of the sub-price index of tradables (P_T), income and human capital are the main influence factors, while the impact of dwelling capacity becomes insignificant (Table 5, columns 2 and 3). Additionally, as with CPI, a north-south trend becomes apparent. Sales of tradable goods may, however, not only depend on own region's income but as well on income in neighbouring regions. According with the market potential concept, distance-weighted income proves to be superior to district income. This income measure becomes significant when spatial dependence is taken into account.

LM tests strongly point to substantial spatial dependence of prices of tradable goods. As the LM(lag) statistic of 7.552 (p=0.006) with district income exceeds the respective value reported in Table 5, spatial autocorrelation of P_T is partially explained by the spatially lagged income. In contrast to the CPI model, the spatial capacity lag has not any explanatory power. Thus, the significance of the spatial price lag (Table 5, column 3) points to spatial dependence mediated by trade. This explanation of spatial price dependence for tradable goods is well in line with the findings of Keller and Shiue (2004) on Chinese rise markets.

The results for the price index of non-tradables (P_{NT}) and the housing price index (P_H) match well with the finding for overall regional price level. According to theory, housing stock exerts a strong negative influence on both sub-price indices. Spatial price dependence is well explained by spatially lagged dwelling capacity. In prices of both goods groups a downward south-north gradient is revealed. The lack of influence of human capital on both sub-price indices may perhaps be due to its stronger demand linkages to high tech goods. However, the role of human capital in determination of price level seems to be not at all clear (see Heston and Aten, 2005).

Table 4: Spatial models for P_T, P_{NT} and P_H

	Spatial price models for tradables		Spatial price models for non-tradables		Spatial housing price models	
Constant	6.110 (12.032)	3.522 (2.445)	6.724 (6.889)	6.138 (7.054)	7.422 (5.326)	6.746 (5.621)
Spatial price lag		0.480 (1.836)				
Income	0.037 (1.537)	0.038 (1.888)	0.062 (3.044)	0.063 (3.989)	0.061 (2.518)	0.065 (2.874)
Housing stock	-0.039 (-1.157)	-0.034 (-1.211)	-0.107 (-1.721)	-0.111 (-2.513)	-0.134 (-2.800)	-0.169 (-2.462)
Spatial stock lag				-0.331 (-3.229)		-0.305 (-2.033)
Human capital	0.064 (3.097)	0.069 (3.982)	0.009 (0.225)		0.046 (1.018)	
Latitude	-0.034 (-3.344)	-0.024 (-2.483)	-0.054 (-2.767)	-0.053 (-2.854)	-0.068 (-2.302)	-0.068 (-2.642)
R^2	0.764	0.776	0.694	0.762	0.683	0.704
SSE	0.0366	0.0299	0.070	0.062	0.090	0.087
L*	42.513	43.500	28.847	31.482	23.679	24.379
AIC	-75.026	-75.000	-47.694	-52.963	-37.358	-38.757
JB	1.445 (0.485)		0.192 (0.909)	2.449 (0.294)	0.300 (0.861)	2.517 (0.284)
BP	0.638 (0.959)	0.480 (0.975)	5.183 (0.269)	3.198 (0.525)	7.078 (0.132)	2.408 (0.661)
LM(lag) / LR(lag)	5.548 (0.019)	1.974 (0.160)	2.321 (0.128)	0.306 (0.580)	3.806 (0.051)	0.682 (0.409)
LM (error)	3.796 (0.051)	2.801 (0.094)	2.063 (0.151)	0.085 (0.770)	3.077 (0.079)	0.628 (0.428)

Notes:
Regression coefficients (z-values in parenthesis), R^2: Coefficient of determination, SER: Standard error of regression, L*: Log likelihood, AIC: Akaike information criterion, JB: Jarque-Bera test, BP: Breusch-Pagan LM test for heteroscedasticity, LM(lag): Robust LM spatial lag test, LR(lag): Likelihood ratio test for spatial lag model, LM(error): Robust LM spatial error test

Although we have allowed for spatial effects in all price level regressions, the estimates may suffer from a simultaneity bias due to endogeneity of income. We have met this problem by treating income as endogenous and employing the method of instrument variables (IV-2SLS). Several regressions are run using contemporaneous exogenous variables and lagged income as instruments. By and large, the IV estimators look very alike independently of income treated as exogenous or endogenous. On the other hand, differences between IV and ML estimation turn out to be large. Most conspicuously, estimators of the spatial autoregressive parameter, ρ, are greater than 1 for all spatial models. Thus, a possible simultaneity bias seems to be minor compared to the loss of accuracy of IV-2SLS estimation instead of ML estimation (Das et al., 2003).

6 Cross-validation of NEG-based price level models

Econometric estimation of NEG-based price level models provides information on the impact of influence factors suggested by the Helpman model. Applying spatial regression models for estimating regional (sub-)price levels across the whole area requires thorough examination of their predictive power. We utilize a cross-validation approach that evaluates out-of-sample forecasts of regional (sub-) price levels. Numerical values of cross-validation criteria may be used as benchmarks for alternative spatial price level models.

The cross-validation approach is conducted using the leave-one-out method (Gao et al., 2006). The procedure consists of three steps. First, spatial price models are estimated with data of n-1 regions. Then, the regression models are applied for predicting the (sub-)price index of the excluded region. At last, predicted and observed (sub-)price levels are compared by means of several cross-validation criteria. The procedure is applied to all spatial price models reported in the preceding section.

Four prediction criteria are used to validate and compare the models:

- the root mean squared prediction error (RMSPE),
- the mean absolute prediction error (MAPE),
- the mean absolute percentage prediction error (MAPPE),
- the correlation coefficient between actual and predicted price level (CORR).

Table 6: Prediction criteria for price level models

(Sub)price index	Model	RMSPE	MAPE	MAPPE	CORR
Consumer price index	Model 1	4.5702	3.5820	4.5444	0.7520
	Model 2	4.3446	3.2464	4.1158	0.7787
	Model 3	4.1096	3.1722	4.0628	0.8062
Price index of tradables	Model 1	4.6369	3.4710	4.1400	0.5989
	Model 2	3.6145	2.8153	3.3872	0.7634
Price index of non-tradables	Model 1	6.1487	4.9500	6.7325	0.7045
	Model 2	5.2578	4.0541	5.5043	0.7954
Housing price index	Model 1	7.2478	5.6101	8.1346	0.7102
	Model 2	6.8926	5.3087	7.7188	0.7431

Notes
RMSPE Root mean squared prediction error, MAPE Mean absolute prediction error, MAPPE Mean absolute percentage prediction error, CORR Correlation coefficient between actual and predicted price level

Table 6 reports the numerical values of the four prediction criteria for the regression models of the consumer price index (CPI) and three sub-price indices. No inconsistency is detected regarding model ranking on the basis of the three error criteria. All cross-validation criteria uniquely point to the preferable model for the respective (sub-)price index. The ranking is, however, not necessarily reflected in the correlation coefficients between the actual and predicted price level leaving out the respective district. Allowing for spatial dependence improves model performance in all cases.

In accordance with the closest approximation to the law of one price, the best spatial model of the sub-price index of tradables has the highest predictive power with regard to the error criteria. On average, the prediction error here amounts to 2.8%. The correlation coefficient between actual and predicted price level leaving out the district under consideration takes a value of 0.76 for this group of goods. By contrast, prediction of the price index of non-tradables and the housing price index turns out to be much more difficult. While the average prediction error increases to 5.5% for the former index, it reaches a value of 7.7% for the latter one. The correlation coefficient is lowest for the housing price index, but second best for the price index of non-tradable goods.

For the consumer price index, the spatial cross-regressive model has a slightly higher predictive power than the spatial lag model. Actual and predicted values of the CPI are strongly correlated ($r \approx 0.80$). The relative prediction error of 4.1% is somewhat larger than that of the best price model for tradables, but well below the MAPPE value for non-tradable goods. Thus, difficulties in making accurate predictions of the (sub-) price index of non-tradables partially carry over to the CPI.

7 Conclusion

Because of a lack of area-wide price level data, regional policy in EU countries has to rely on nominal income data. From scattered samples on regional price level it is known that cost of living is often above average in high income areas. In this case, disparities in standard of living revealed from nominal measures can be considerably distorted. Regional promotion programs are expected to be differently tailored when based on real quantities. Thus, regional policy may benefit from econometric studies on determinants of regional price level. For spatial planning policy, additionally knowledge on spatial disparities in prices of housing and other goods groups is informative.

The present paper investigates regional varying cost of living based on NEG theory. Price level models for the consumer price index as well as prices of tradables, non-tradables and housing are estimated and calibrated using data of a Southern German sample. As well as Keller and Shiue (2004) we find strong evidence for the presence of spatial effects in regional price formation. The goodness of fit is comparable to that of models used in international price comparisons (cf. Aten and Heston, 2005). A cross-validation shows error rates in out-of-sample forecasts between about 3 1/2 and 8 per cent. The best predictions are obtained for the price index of tradable goods, while the largest prediction errors are associated with the housing price index.

As expected all price indices are strongly linked with income. For the prices of tradables, market potential, measured by distance-weighted income, turns out to be preferable to regional income. While housing stock is relevant for overall price level and the sub-price indices of non-tradables and housing, it becomes insignificant in explaining the prices of tradable goods. The latter are additionally explained human capital often chosen as a control variable in price comparisons.

While regional heterogeneity is captured by a south-north price gradient in all price models, spatial price correlation is modelled in different forms. Spatial dependence in overall price level and prices of non-tradables and housing can be attributed to spatially lagged dwelling capacity. By contrast, spatial dependence in prices of tradables tends to be mediated by trade.

In contrast to the prediction of the Helpman model, housing stock seems not to be neutral with respect to overall price level. Significant negative influence of housing stock on CPI points to some weakness of modelling the non-tradable goods sector. Cost of living may in fact be negatively affected by housing scarcity in centres. Thus, the strength of the centripetal force represented by housing tends to be underrated in the Helpman model.

References

Anselin, L. (1988a), Spatial Econometrics: Methods and Models. Kluwer, Dordrecht et al.

Anselin, L. (1988b), Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity. Geographical Analysis 20: 1-17.

Anselin, L. (1992), Spacestat: A Program for Statistical Analysis of Spatial Data. Santa Barbara, CA, NCGIA.

Anselin, L. (1995), Local Indicators of Spatial Association – LISA. Geographical Analysis 27: 93-115.

Anselin, L. (2003), Spatial Externalities, Spatial Multipliers, and Spatial Econometrics. International Regional Science Review 26, 153-166.

Anselin, L., Florax, R.J.G.M. (1995), Small Sample Properties of Tests for Spatial Dependence in Regression Models: Some Further Results, in: Anselin, L., Florax, R.J.G.M. (eds.), New Directions in Spatial Econometrics. Springer, Berlin et al.: 21-74.

Anselin, L., Bera, A.K., Florax, M., Yoon, M.J. (1996), Simple Diagnostic Tests for Spatial Dependence. Regional Science and Urban Economics 26: 76-104.

Aten, B.H. (1996), Evidence of Spatial Autocorrelation in International Prices. Review of Income and Wealth 42: 149-163.

Aten, B.H. (2001), An Application of the Spatial Expansion Method to Regional Price Level Estimates, North American Regional Science Annual Meeting. Charlotte, SC.

Aten, B.H., Heston, A. (2003), Identifying Spatial Commonalities: An Empirical Application to Inter and Intra-Country Data, WIDER Project Meeting on Spatial Inequality in Development. Helsinki, Finland.

Aten, B.H., Heston, A. (2005), Regional Output Differences in International Perspective, in: Kanbur, R. and Venables, A.J. (eds.), Spatial Inequality and Development, UNU-Wider Studies in Development Economics. Oxford University Press, New York: 15-36.

Bang, J.T. (2005), Do Preferential Trade Agreements Divert Trade? Working Paper, University of Illinois, Urbana-Champaign.

BSMWVT (2003), Die reale Kaufkraft in Bayern 2002 – Zwischenörtliche Preis- und Einkommensunterschiede. Bayerisches Staatsministerium für Wirtschaft, Verkehr und Technologie, München.

Beck, N., Gleditsch, K.S., Beardsley, K. (2004), Space is more than Geography: Using Spatial Econometrics in the Study of Political Economy. http://www.nyu.edu/gsas/dept/politics/faculty/beck/becketal.pdf.

Bera, A.K., Yoon, M.J. (1993), Specification Testing with Locally Misspecified Alternatives. Econometric Theory 9: 649–658.

Brakman, S., Garretsen, H., Schramm, M. (2004), The Spatial Distribution of Wages: Estimating the Helpman-Hanson Model for German. Journal of Regional Science 44: 437-466.

Cliff, A. und Ord, J.K. (1981), Spatial Processes: Models and Applications. Pion, London.

Conley, T.G., Ligon, E. (2002), Economic Distance and Cross-Country Spillovers. Journal of Economic Growth 7: 157-187.

Cook, R.D., Weisberg, S. (1982), Residuals and Influence in Regression. Chapman and Hall, London.

Das, D., Kelejian, H.H., Prucha, I.R. (2003), Finite Sample Properties of Estimators of Spatial Autoregressive Models with Autoregressive Disturbances. Papers in Regional Science 82: 1-26.

Fingleton, B. (1999), Spurios Spatial Regression: Some Monte Carlo Results with a Spatial Unit Root and Spatial Cointegration. Journal of Regional Science 39: 1-19.

Fingleton, B. (2004), The New Economic Geography versus Urban Economics: An Evaluation Using Local Wage Rates in Great Britain. Working Paper, University of Cambridge, UK.

Fujita, M., Krugman P.R., Venables, A.J. (1999), The Spatial Economy: Cities, Regions and International Trade, MIT Press, Cambridge, MA.

Fujita, M., Thisse, J.-F. (2002), Economics of Agglomeration: Cities, Industrial Location, and Regional Growth. Cambridge University Press, Cambridge, UK.

Gao, X., Asami, Y., Chung, C.-J. F. (2006), An Empirical Evaluation of Spatial Regression Models, Computer and Geosciences 32, 1040-1051.

Getis, A., Ord, J.K. (1992), The Analysis of Spatial Association by Use of Distance Statistics. Geographical Analysis 24: 189-206.

Getis, A. (1995), Spatial Filtering in a Regression Framework: Examples Using Data on Urban Crime, Regional Inequality and Government Expenditures, in: Anselin, L., Florax, R. (eds), New directions in spatial econometrics. Springer, Berlin et al.: 172-185.

Gimpel, J.G., Schuknecht, J.E. (2003), Political Participation and the Accessibility of the Ballot Box. Political Geography 22: 471-488.

Haining, R. and Wise, S. (1997) Exploratory Spatial Data Analysis, NCGIA Core Curriculum in GIScience. http://www.ncgia.ucsb.edu/giscc/units/u128/u128.html.

Hanson, G. (2005), Market Potential, Increasing Returns, and Economic Concentration. Journal of International Economics 67: 1-24.

Helpman, E. (1998), The Size of Regions, in: Pines, D., Sadka, E. and Zilcha, I. (eds.), Topics in Public Economics. Cambridge University Press, Cambridge: 33-54.

Heston, A., Nuxoll, D.A. and Summers, R. (1994), The Differential-Productivity Hypothesis and Purchasing-Power Parities: Some New Evidence. Review of International Economics 2: 227-243.

Isard, W. et al. (1998), Methods of Interregional and Regional Analysis. Ashgate, Aldershot, UK.

Johnston, R., McKinney, M., Stark, T. (1996), Regional Price Level Variations and eal Household Income in the United Kingdom, 1979/80-1993, Regional Studies 30, 567-578.

Jones, C.I. (2002), Introduction to Economic Growth, 2nd ed. Norton, New York.

Jones, J.P., Casetti, E. (1992), Applications of the Expansion Method. Routledge, London.

Keller, W., Shiue, C.H. (2004), The Origins of Spatial Interaction - Evidence form Chinese Rice Markets, 1742-1795, NBER Working Paper No.10069, forthcoming: Journal of Econometrics.

Krugman, P.R. (1991), Increasing Returns and Economic Geography. Journal of Political Economy 99: 483-499.

LeSage, J.P. (1999), The Theory and Practice of Spatial Econometrics. University of Toledo, http://www.spatial-econometrics.com.

Marshall, A. (1920), Principles of Economics, 8th ed. MacMillan Press Ltd., London. Reprinted 1990, Porcupine Press, Philadelphia.

McCann, P. (2001), Urban and Regional Economics. Oxford University Press, Oxford.

Mion, G. (2004), Spatial Externalities and Empirical Analysis: The Case of Italy. Journal of Urban Economics 56: 97-118.

Morenoff, J.D., Sampson, R.J., Raudenbusch, S.W. (2001), Neighbourhood Inequality, Collective Efficacy, and the Spatial Dynamics of Urban Violence. Research Report No. 00-451, PSC Population Studies Center, Institute for Social Research, University of Michigan.

Mühr, B. (2005), Klimadiagramme, Institut für Meteorologie und Klimaforschung der Universität Karlsruhe (in cooperation with the Forschungszentrum Karlsruhe). http://imkhp2.physik.uni-karlsruhe.de/~muehr/wetter.html.

Niebuhr, A. (2004), Market Access and Regional Disparities – New Economic Geography in Europe. HWWA Discussion Paper 269, Hamburg.

Robert-Nicoud, F. (2004), The Structure of Simple 'New Economic Geography' Models. CEPR Discussion Paper series 4326, London.

Roos, M. (2001), Wages and Market Potential in Germany. Jahrbuch für Regionalwissenschaft 21: 171-195.

Sen, A., Smith, T.E. (1995), Gravity Models of Spatial Interaction Behavior. Springer, New York.

Ströhl, G. (1994), Zwischenörtlicher Vergleich des Verbraucherpreisniveaus in 50 Städten. Wirtschaft und Statistik 6/1994: 415-434.

Suedekum, J. (2004), Agglomeration and Regional Costs-of-Living. Discussion Paper, University of Konstanz.

Tabuchi, T. (2001), On Interregional Price Differentials. Japanese Economic Review 52: 104-115.

Tobler W. (1979), Cellular Geography, in: Gale, S., Ollson, G. (eds), Philosophy in Geography. Reidel, Dordrecht: 379-386.

Upton, G. J., B. Fingleton (1985), Spatial Data Analysis by Example, Volume I. Wiley, New York et al.

Zhang, J., Kristensen, G. (1995), A Gravity Model with Variable Coefficients: The EEC Trade with Third Countries. Geographical Analysis 27: 307-320.

Appendix

Table A1: Size classes of municipalities

Size class	Municipality	Number of price representatives
A	Deggendorf, Neuburg a. d. Donau, Lohr a. Main, Bad Reichenhall, Neustadt b. Coburg, Cham, Dinkelsbühl	109
G	Regensburg, Würzburg, Bamberg, Bayreuth, Schweinfurt, Landshut, Passau, Weiden i. d. Opf., Ansbach, Rosenheim, Lindau	204
K	Munich, Nuremberg, Augsburg	646

Notes
Size class A: rural district, size class G: urban district (population < 250 000), size class K: urban district (population > 250 000). Source: BSMWVT (2003).