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Testing Nonlinear New Economic Geography Models

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Abstract

We test a New Economic Geography (NEG) model for U.S. counties, employing a new strategy that allows us to bring the full NEG model to the data, and to assess selected elements of this model separately. We find no empirical support for the full NEG model. Regional wages in the U.S. do not respond to local wage shocks in the way predicted by the model. We show that the main reason for this is that the model does not predict either the migration patterns induced by local wage shocks or the repercussions of this migration for regional wages correctly.

Keywords
New economic geography, spatial econometrics

JEL Classification
C21, C51, R12

Contents

1 Introduction[1]

Theory is still ahead of empirics in New Economic Geography (NEG). Following Paul Krugman's seminal article on "Increasing Returns and Economic Geography" (Krugman 1991), a vibrant theoretical literature has been developing a rich variety of general equilibrium models that explain the spatial distribution of economic activity by the interplay of microeconomically well-founded centripetal and centrifugal forces.[2] The centripetal forces, which tend to reinforce each other, are the "home market effect", according to which firms who produce under increasing returns to scale are attracted to cities where they can sell larger shares of their output to local consumers at comparatively low transport costs, and the "price index effect", according to which consumers who love variety in consumption goods are attracted to cities because they can purchase larger shares of their consumption bundles from local producers at comparatively low transport costs. The centrifugal forces are the "competition effect", according to which firms are discouraged from locating in cities where they face fiercer price competition with other producers, and the "congestion effect", according to which consumers are discouraged from locating in cities where they face higher costs of local consumption goods. The micro-foundation of the centripetal and centrifugal forces makes these NEG models particularly appealing for economists and policy makers. These forces do not result from abstract economies or diseconomies of agglomeration, or from knowledge spillovers that are themselves black boxes. They result from scale economies within firms, imperfect competition, and transport costs.

The empirical literature has made only limited progress in assessing the empirical relevance of NEG, by contrast. The main reason for this is that theoretical models with scale economies and imperfect competition typically do not lend themselves easily to direct empirical testing. They do not have closed-form solutions that can be brought directly to the data (Fujita et al. 1999: 347). The present paper contributes to this empirical literature on testing NEG models. It proposes a new strategy of bringing NEG models to the data and of testing them more rigorously, and uses this strategy to test a multiregion nonlinear Krugman-type NEG model taken right out of the textbook by Fujita, Krugman, and Venables (Fujita et al. 1999, Chapter 4) for a panel of U.S. counties over the period 1990–2005.

The empirical NEG literature so far has developed three main alternative strategies to test propositions of NEG models, which may be labeled regression-based, simulation-based, and hybrid strategy. The regression-based strategy is to test partial equilibria or selected propositions of NEG models (e.g., Davis

[1] We would like to thank Frank Bickenbach, Bernard Fingleton, Paul Kramer, Thierry Mayer, and Stephen Redding for helpful comments and suggestions.

[2] See the textbooks by Fujita et al. (1999), Baldwin et al. (2003), Combes et al. (2008), or Brakman et al. (2009), among others.

and Weinstein 1999, 2003, Hanson 2005, Redding and Venables 2004).[3] Studies pursuing this strategy use information from the NEG model rather sparsely but data on observable endogenous variables of this model rather extensively. They approximate the equilibrium values of observable endogenous variables of the model by empirical data rather than taking into account the equilibrium conditions of the model that determine these equilibrium values in terms of parameters and exogenous variables. As a consequence of regressing an endogenous variable on other endogenous variables, these studies are, on the one hand, able to estimate all or most of the structural parameters of the NEG model but are, on the other hand, plagued by serious endogeneity problems. Since these studies account for the rich variety of interdependencies between wages, prices, income, and employment within and across regions featured by NEG models only to a limited extent,they are not suited too well for assessing to what extent the observed spatial concentration of employment and the urban-rural wage gradients are actually due to the home market and price index effects. For example, the estimation results obtained by studies that employ this regression-based strategy to estimate the wage equation[4] are virtually invariant to whether labor is assumed to be mobile or immobile in the underlying NEG model. Studies that assume labor to be immobile, such as Redding and Venables (2004), obtain virtually the same result as those that assume labor to be immobile, such as Hanson (2005), Mion (2004) or Head and Mayer (2006). Labor mobility makes a big difference in theoretical models, though. The centripetal forces that are responsible for the emergence of urban agglomeration and an urban-rural wage gradient effectively unfold in NEG models only if workers do actually respond by migration to regional differences in real wages. If they do not migrate to places with thicker markets and higher real wages, NEG models have little to contribute to explaining urban agglomeration.

The simulation-based strategy is to fit simulated general equilibria of NEG models to data for a single observable endogenous variable (e.g., Stelder 2005, Redding and Sturm (2008). Studies pursuing this strategy use information from the NEG model rather extensively but data on observable endogenous variables of this model rather sparsely. Redding and Sturm, for example, calibrate an NEG model to the observed regional distribution of a single endogenous variable, population, at a specific point in time. They then simulate a real-world shock and check if the model predicts the observed changes of the regional distribution of population following the shock correctly. Focusing on data for a single endogenous variable, they do not rule out the possibility that the simulated general equilibrium of the NEG model replicates the spatial distributions of other endogenous variables rather poorly.

[3] These studies are surveyed in Head and Mayer (2004), Brakman et al. (2009), Brülhart (2009), and Redding (2009), among others.

[4] The wage equation, one of the central equilibrium conditions of NEG models, establishes a positive relationship between the nominal wage rate and the real market potential (RMP) of a region at given regional distributions of prices, income, and employment. A region's RMP is the aggregate real demand from all regions for the goods produced in this region at mill prices.

The hybrid strategy, invented recently by Behrens et al. (2009), involves a combination of elements of the regression- and the simulation-based strategies. This strategy is to estimate a subset of the structural parameters of the NEG model from a single equilibrium condition of the NEG model, which is constrained by simulated equilibrium values of other endogenous variables. Behrens et al. iteratively estimate the transport cost parameter from the trade equation, an equilibrium condition that determines bilateral trade intensities between regions from the economic masses of these regions and the transport costs between them.[5] Rather than quantifying the economic masses by observable economic indicators in the regression model, they calculate them from the respective equilibrium conditions of the NEG model, taking ionto account the transport cost parameter estimated in the previous iteration. By iteratively updating the transport cost parameter and the economic masses of all regions, they eventually obtain the equilibrium transport cost parameter that solves the trade equation stochastically and the other equilibrium conditions deterministically. This hybrid strategy combines some of the advantages but also some of the disadvantages of the regression- and the simulation-based strategies. On the one hand, it takes, like the simulation-based strategy, into account the rich variety of interdependencies between variables and regions in the NEG model. And it facilitates, like the regression-based strategy, estimating structural parameters of the NEG model directly. On the other hand, it takes, like the simulation-based strategy, empirical information only rather sparsely into account. The only empirical information it utilizes is bilateral trade intensities, while the other endogenous variables are determined solely from the theoretical model, and are not confronted with the data.

The present paper pursues a new, fourth strategy to test NEG models. This strategy facilitates a more rigorous assessment of the empirical relevance of NEG than the other strategies. It takes, like the regression-based strategy, empirical information on observable endogenous variables extensively into account, and facilitates estimation of structural parameters. At the same time, it takes, like the simulation-based and the hybrid strategies, the entire set of equilibrium conditions of the NEG model into account. The "trick" that allows us to take both data and theory extensively into account is that we Taylor–approximate the NEG model at its general equilibrium, quantifying the equilibrium values of the observable endogenous variables by the data.[6] This trick allows us to reduce, for any set of predetermined structural parameters, all the equilibrium conditions of the NEG model to a single, fully parameterized equation, a reduced-form linearized wage equation. This reduced-form linearized wage equation maps the

[5] The theoretical model in Behrens et al. (2009) differs from those discussed so far in that it features heterogeneous firms, immobile labor, and border effects.

[6] We approximate the equilibrium values of the endogenous variables of the NEG model by their observed long-run averages, which we assume to be exogenous to simplify the estimations. Taylor approximation has been used before by Combes and Lafourcade (2008) and Mion (2004) to escape nonlinerarity of their regression models. These studies approximate their models at a perfect-integration equilibrium with zero trade costs, however.

full (linearized) NEG model into parametric restrictions on the interdependencies between wages in all regions. To find the set of predetermined structural parameters that solves the NEG model, we estimate this reduced-form wage equation iteratively for different sets of structural parameters. Each iteration gives us an estimate of one of the structural parameters, the substitution elasticity. We take the NEG model to be solved, if this estimated substitution elasticity has the same value as the predetermined substitution elasticity used to derive the reduced-form wage equation from the equilibrium conditions of the NEG model. The estimation of the reduced-form wage equation for the set of parameters that solves the model also gives us information on how well the NEG model fits the data.

The reduced-form linearized wage equation is a simple spatial autoregressive model of order one—SAR(1)—in short-run deviations of local wages from their equilibrium values. It relates these deviations in each region to the weighted sum of the deviations in all regions. The (spatial) weights are the parametric restrictions derived from the NEG model for given equilibrium values of the endogenous variables and given parameters. They are bilateral elasticities of the wage rate in one region with respect to the wage rate in another region. Estimation of the SAR(1) model thus boils down to a test of whether or not local wage shocks propagate through the system of observed regional wages in the way predicted by the NEG model. If NEG has something to contribute to explaining regional interdependencies through trade and migration, the extent to which wage shocks spill over to neighboring regions should not just depend on geographical distances. It should depend on the relative trade intensities between all regions and the relative attractiveness of all regions for mobile workers in the way hypothesized by the NEG model. We will consequently conclude that the NEG model contributes to explaining the regional distributions of economic activity and wages, if the SAR(1) model derived from the NEG model fits the data better than a theoryless SAR(1) model where the extent to which a local shocks spill over to neighboring regions depends only on geographical distances.

The strategy we use in this paper facilitates not only empirical evaluations of non-linear NEG models as a whole. It also facilitates evaluations of selected elements of these models separately. Even if the NEG model as a whole does not contribute to explaining the regional distributions of economic activity and wages, some of its elements may still help us understand better which forces and mechanisms shape these regional distributions. By evaluating selected elements of NEG models, we aim at identifying those elements of the models that contribute to explaining the regional distributions of economic activity and wages, and those that do not.[7] We evaluate two elements of NEG models in the present

[7] This evaluation of elements of NEG models is what Fujita, Krugman and Venables call for in the concluding chapter of their classical textbook: Referring to an earlier version of Hanson (2005), the argue that "We clearly need much more such work, as closely tied to the theoretical models as possible, as a way of sorting through which of the intriguing possibilities suggested by the sorts of models developed in this book are truely relevant, as well as to indicate where further elaboration of the models is necessary" (Fujita et al. 1999: 347).

paper, the effects of labor mobility and of changes of consumer prices. For this purpose, we evaluate if the full, unrestricted NEG model just described fits the data better than restricted versions of this model where the elements to be evaluated are "switched off" by assuming labor to be immobile and/or prices to be fixed. We will conclude that the respective element under evaluation contributes to explaining the regional distributions of economic activity and wages, if the unrestricted model fits the data better than a restricted version of the same model where this and only this element is switched off. We bring the restricted versions of the NEG model to the data in the same way as we bring the full model to the data. We map each restricted version into a separate SAR(1) model, which differs from the SAR(1) model that represents the full NEG model only in the values of the spatial weights, i.e., in the magnitudes of the interdependencies between regional wages hypotheszized by the model. Provided an equilibrium exists for each of the two models to be compared to each other, we will conclude that a specific element of the NEG model contributes to explaining the regional distributions of economic activity and wages, if the SAR(1) model that represents the NEG model inclusive of this element fits the data better than the alternative SAR(1) model that represents the NEG model exclusive of this element.

This paper adds not only to the empirical NEG literature in that it demonstrates how NEG models can be brought to the data more rigorously. It also adds to the spatial econometrics literature in that it demonstrates how spatial weights can be derived consistently from economic theory. Most empirical studies that have taken spatial interdependencies into account have done so in a rather ad hoc fashion. Lacking a theoretical foundation of the spatial interdependencies, they have approximated them by geographical characteristics like distances or administrative characteristics like common borders. We aim at explaining them by economic theory.

We test the most basic NEG model, which was developed by Krugman (1991) for two regions and extended to many regions in Fujita et al. (1999, Chapter 4) for U.S. counties. We prefer testing this model for regions in the U.S. rather than in Europe or Japan because the U.S. arguably meets the assumptions of the theoretical model fairly well. It has a large market where trade and migration are not impeded notably by border impediments, and where workers are arguably more mobile than in other developed countries (Obstfeld and Peri 1998). Following most of the studies that employ the regression-based strategy to test NEG models, we estimate our SAR(1) models for a pool of annual data which comprises the 16 years from 1990 to 2005. A sample time period of 16 years is long enough to limit the effects of outliers, and short enough to justify our assumption that the U.S. economy is characterized by a single, time-invariant equilibrium. Our choice of annual data implies that we evaluate the NEG models by means of those responses of wages to local wage shocks that materialize in the same years as the shocks. Since it may take more than a single year to fully work off shocks, we allow the endogenous variables of the

NEG model to adjust only partially to their equilibrium values implied by the NEG model in our empirical investigation. That is, we evaluate if the data support the directions and relative (rather than absolute) magnitudes of the changes in endogenous variables predicted by the NEG models. We expect that at least a small fraction of the total price effects and of the total migration flows needed to restore equilibrium model materialize in the same year as the shock.

Our results are less favorable for NEG than those of many previous studies that adopted other, less rigorous strategies to assess NEG models. Even though we allow for partial adjust of the endogenous variables of the NEG model, the SAR(1) model that represents the full NEG model fits the data worse than the theoryless SAR(1) model. Our assessments of individual elements of the NEG model show that the main reason for the poor fit of the full model is that the NEG model apparently does not get the incentives for, or the consequences of interregional migration right. A restricted NEG model where labor is assumed to be regionally immobile fits the data fairly well for plausible values of the structural parameters. It fits the data better than the full, unrestricted NEG model, and also better than the theoryless model.

The plan of this paper is as follows. Section 2 sketches the theoretical NEG model. Section 3 derives several empirical SAR(1) model from the entie NEG model as well as from restricted versions of this model. Section 4 discusses econometric issues and describes the data. Section 5 presents and discusses the results, and Section 6 concludes.

2 Theoretical model

We test a standard multiregion Krugman-type NEG model with R regions, indexed by r ($r = 1, ..., R$), two sectors, agriculture and manufacturing, and two types of workers, agricultural and manufacturing workers. This model is presented in detail in Chapter 4 of Fujita et al. (1999) and will be sketched only briefly here. In the agricultural sector, a fixed number of immobile workers produces a homogeneous agricultural good at constant returns to scale. Each region is equipped with a fixed number of L_r^A agricultural workers, each of which produces one unit of the agricultural good. The agricultural good is traded freely across regions. The agricultural wage rate is consequently equal to the price of the agricultural good, which is the same in all regions, and is normalized to one. The monopolistically competitive manufacturing sector produces a heterogeneous manufacturing good under increasing returns to scale using regionally mobile manufacturing workers as the only input. Each firm in the manufacturing sector produces exclusively one variety of the manufacturing good that substitutes imperfectly for other varieties of the manufacturing good produced by other firms in the same or in other regions. The manufacturing good is traded freely within a region but at positive, distance-related iceberg transport costs across regions. The consumers in all regions have identical Dixit-Stiglitz preferences, reflected by a nested Cobb-Douglas-CES utility function that features love of variety.

The general equilibrium solution of this model requires solving the following system of $3R$ equations that determine nominal wage rates and employment in the manufacturing sector, w_r and L_r^M, in all R regions, and consumer price indices (CPIs) for traded manufacturing goods, G_r, in all R regions:

$$
\begin{aligned}
w_r &= C_1 \left[\sum_{s=1}^{R} T_{sr}^{1-\sigma} G_s^{\sigma-1} \left(w_s L_s^M + L_s^A \right) \right]^{\frac{1}{\sigma}}, && (1) \\
G_r &= C_2 \left[\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M \right]^{\frac{1}{1-\sigma}}, && (2) \\
\frac{w_r}{G_r^{\mu}} &= \frac{w_i}{G_i^{\mu}}, \qquad i \neq r, && (3) \\
\sum_{r=1}^{R} L_r^M &= L^M, \qquad r = 1, ..., R, && (4)
\end{aligned}
$$

where $C_1 = \mu^{\frac{1}{\sigma}} C_2^{\frac{1-\sigma}{\sigma}}$, and $C_2 = \frac{c}{\sigma-1} \left(\sigma^{\sigma} F \right)^{\frac{1}{\sigma-1}}$. T_{rs} $[= T(D_{rs}, \tau) > 1]$ denotes the distance-related iceberg transport costs for shipping one unit of the manufacturing good from region s to region r (D_{rs}: distance from region s to region r; τ: unit-distance transport costs parameter). L^M denotes the total number of manufacturing workers in the economy, σ the elasticity of substitution between any two varieties of the manufacturing good, μ the expenditure share spent on the manufacturing good ($1-\mu$: share spent on the agricultural good), and c and F the marginal and fixed costs of producing one unit of a variety of the manufacturing good.

Equation (1) is the wage equation or, more precisely, the wage rate offered by a representative producer of the manufacturing good in region r. It determines the wages in all regions for given income and given prices of the manufacturing varieties. We have substituted the equilibrium condition that determines nominal income, $Y_s = w_s L_s^M + L_s^A$, directly into the wage equation for the sake of brevity. The wage equation takes into account the producer's optimal production plan at zero profits as well as the product market equilibrium for the manufacturing varieties. Equation (2) determines the CPI for the manufacturing varieties in region r for a given regional distribution of manufacturing employment and given regional wages. It takes into account that the equilibrium size of manufacturing firms is the same in all regions, which implies that the number of varieties produced in each region is directly proportional to the number of manufacturing workers in this region. It also takes into account that all manufacturing firms in a region charge the same equilibrium mill price for their varieties. This price is directly proportional to the regional wage rate.

Equations (3) and (4) jointly determine the regional distribution of manufacturing workers. (3) is the no-migration condition, which requires that real wages are the same in all R regions, or, equivalently, that real wages in all regions are the same as in a benchmark region i. Any inequality in real wages is assumed to trigger migration of manufacturing workers to the regions with higher real wages. Finally, (4) is the labor-market-clearing condition.

3 Empirical Model

3.1 Full model

The strategy to test NEG models we use in this paper brings the whole NEG model, characterized by its equilibrium conditions (1)-(4), to the data. We essentially estimate a reduced form of the log of the wage equation (1) after linearizing it by first-order Taylor approximation, and after replacing the endogenous right-hand side variables, namely the price indices, G_s, and manufacturing employment, L_s^M, in all regions, by expressions derived from equations (2)-(4). These expressions depend only on variables that we assume to be exogenous, except regional wages. Eliminating the endogenous right-hand side variables allows us not only to capture all general equilibrium effects implied by the theoretical model but also to avoid endogeneity biases in the estimation caused by imperfectly instrumented endogenous explanatory variables.

The Taylor approximation of the logged wage equation at the general equilibrium of this model yields a SAR model of order one in the deviations of the (logged) wage rates in all regions from their equilibrium values:

$$\ln w_r - \ln \widetilde{w}_r \approx \sum_{x=1}^{R} \frac{\partial \ln w_r}{\partial \ln w_x} \left(\sigma, \mu, \mathbf{T}, \mathbf{L}^A, \widetilde{\mathbf{w}}, \widetilde{\mathbf{L}^M} \right) \ (\ln w_x - \ln \widetilde{w}_x), \qquad (5)$$

$r = 1, ..., R$, or

$$\ln \mathbf{w} - \ln \widetilde{\mathbf{w}} \approx \mathbf{J}^w (\ln \mathbf{w} - \ln \widetilde{\mathbf{w}}), \qquad (6)$$

in matrix notation. This SAR(1) model constitutes the core of our regression model. A tilde characterizes equilibrium values. Equation (5) explains the deviation of the (logged) wage rate in any region r from its equilibrium ($\ln w_r - \ln \widetilde{w}_r$) by the weighted sum of the deviations of the (logged) wage rates in all regions x, $x = 1, ..., R$, from their equilibria. The weights are $\frac{\partial \ln w_r}{\partial \ln w_x}$, the bilateral elasticities of the wage rate in any region r with respect to the wage rate in any region x. These bilateral weights, which are collected in the spatial weights matrix $\mathbf{J}^w = (\frac{\partial \ln w_r}{\partial \ln w_x}(\cdot))_{(R \times R)}$ in (6), depend on all the parameters and variables in the NEG model. More precisely, each bilateral spatial weight $\frac{\partial \ln w_r}{\partial \ln w_x}$ depends on (i) all the structural parameters of the NEG model, which are the substitution elasticity σ, the income share spent on the manufacturing good, μ, the full matrix of exogenous bilateral transport costs, $\mathbf{T} = (T_{sr})_{(R\times R)}$, (ii) the realizations of the exogenous variable, agricultural employment, in all regions, $\mathbf{L}^A = (L_r^A)_{(R\times 1)}$, and (iii) the realizations of the equilibrium wage rates and employment quantities in the manufacturing sector in all regions, $\widetilde{\mathbf{w}} = (\widetilde{w}_r)_{(R\times 1)}$ and $\widetilde{\mathbf{L}^M} = (\widetilde{L_r^M})_{(R\times 1)}$. For the SAR(1) model (5) to be estimable, all these parameters and variables must be predetermined and assumed to be exogenous.

We derive the spatial weights matrix $\frac{\partial \ln w_r}{\partial \ln w_x}$ from the equilibrium conditions (1)–(4) of the NEG model in the following way (see Appendix 1 for the technical details): First, we totally differentiate the logged wage equation in (1) for all pairs of regions r and x, which yields

$$\frac{\partial \ln w_r}{\partial \ln w_x} = \frac{1}{\sigma}\left(f_{rx}^y + \sum_{s=1}^{R} f_{rs}^y \frac{\partial \ln L_s^M}{\partial \ln w_x} + \sum_{s=1}^{R} f_{rs}^g \frac{\partial \ln g_s}{\partial \ln w_x} \right), \tag{7}$$

or

$$\mathbf{J}^w = \frac{1}{\sigma}\left[\mathbf{f}^y + \mathbf{f}^y\mathbf{J}^L + \mathbf{f}^g\mathbf{J}^g\right] \tag{8}$$

in matrix notation,[8] and substitute (7) into (5).[9] According to (7), the elasticity of the wage rate in a region r with respect to the wage rate in a region x, $\frac{\partial \ln w_r}{\partial \ln w_x}$, depends on three terms. The first two terms reflect the effects of regional income on wages in region r at given prices of all varieties, and the third term reflects the effects of prices of all varieties on wages in region r at given regional income. The first term, f_{rx}^y ($f_{rx}^y \geq 0$), reflects what we will henceforth call the "wage-induced income effect" of a wage shock in region x. A positive wage shock in x allows firms in r to pay, ceteris paribus, higher wages because it raises nominal income of all manufacturing workers in x and thereby nominal demand from x for the varieties produced in r. f_{rx}^y is the share of all manufacturing workers from region x in the real market potential of region r. The second term, $\sum_{s=1}^{R} f_{rs}^y \frac{\partial \ln L_s^M}{\partial \ln w_x}$, summarizes what we will henceforth call "migration-induced income effects". It reflects the wage effects of income changes in all regions induced by the migration flows triggered by a wage shock in region x. A positive wage shock in x allows firms in r to pay, ceteris paribus, higher wages if it raises demand for the varieties produced in r by inducing net migration flows to those regions whose consumers buy more extensively from r. $\frac{\partial \ln L_s^M}{\partial \ln w_x}$ ($\frac{\partial \ln L_s^M}{\partial \ln w_x} \lesseqgtr 0$) is the elasticity of employment in region s with respect to the wage rate in region x, which will be discussed below in more detail, and f_{rs}^y ($f_{rs}^y \geq 0$) is, similar to f_{rx}^y, the share of all manufacturing workers from region x in the real market potential of region r. The elasticity $\frac{\partial \ln L_s^M}{\partial \ln w_x}$ will be zero, if labor is assumed to be immobile in the

[8] All bold variables in (8) and the subsequent expressions in matrix notation, (10), (12), and (13) denote $(R \times R)$ matrices. Like the matrix $\mathbf{J}^w$, the matrix $\mathbf{c}^w$, for example, collects all R^2 variables c_{rx}^w, $r, x = 1, ..., R$.

[9] g_s differs from G_s only by a constant that does not affect the results.

underlying NEG model. The third term, finally, $\sum_{s=1}^{R} f_{rs}^{g} \frac{\partial \ln g_s}{\partial \ln w_x}$, summarizes the effects of all changes in the regional price indices (CPIs) induced by a wage shock in region x. A positive wage shock in x allows firms in r to pay, ceteris paribus, higher wages if it strengthens their competitiveness by raising the CPIs in r's main export markets particularly strongly. The term $\frac{\partial \ln g_s}{\partial \ln w_x}$ ($\frac{\partial \ln g_s}{\partial \ln w_x} \lesseqgtr 0$) is the elasticity of the CPI in region s with respect to the wage rate in region x, which will be discussed below in more detail, and f_{rs}^{g} ($f_{rs}^{g} \geq 0$) is the share of region s in region r's real market potential. The term $\frac{\partial \ln g_s}{\partial \ln w_x}$ will be zero, if prices of the manufacturing good are assumed to be fixed in the underlying NEG model.

Second, to eliminate $\frac{\partial \ln g_s}{\partial \ln w_x}$ from (7), we totally differentiate the logged price index in (2) for all pairs of regions r and x, which yields

$$\frac{\partial \ln g_r}{\partial \ln w_x} = c_{rx} + \frac{1}{1-\sigma} \sum_{s=1}^{R} c_{rs} \frac{\partial \ln L_s^M}{\partial \ln w_x}, \tag{9}$$

or

$$\mathbf{J}^g = \mathbf{c}^g + \frac{1}{1-\sigma} \mathbf{c}^g \mathbf{J}^L \tag{10}$$

in matrix notation. According to (9), the elasticity of the CPI in a region r with respect to the wage rate in region x depends on two terms. The first term, c_{rx} ($c_{rx} \geq 0$), is what we will henceforth call the "wage-induced price effect". It reflects the direct effects of production costs in region x on the price level in region r. A positive wage shock in x raises, ceteris paribus, the CPI in region r the more, the more extensively consumers in r buy from x. c_{rx} is the share of region x in region r's CPI. The second term, $\frac{1}{1-\sigma} \sum_{s=1}^{R} c_{rs} \frac{\partial \ln L_s^M}{\partial \ln w_x}$, summarizes what we will henceforth call "migration-induced price effect". It reflects the direct and indirect effects of migration on the intensity of competition in region r. A positive wage shock in x raises the price index in r if it triggers net out-migration from r's main suppliers. This out-migration reduces the number of varieties produced in these regions, which in turn reduces the intensity of competition among the producers serving region r.

And third, to eliminate $\frac{\partial \ln L_s^M}{\partial \ln w_x}$ from (7) and (9), we totally differentiate the $R-1$ independent logged no-migration conditions in (3) and the loffed labor-market clearing condition (4) jointly for all pairs of regions r and x, which yields

$$0 = \mu c_{rx}^{L} + \frac{\mu}{1-\sigma} \sum_{s=1}^{R} b_{rs}^{L} \frac{\partial \ln L_s^M}{\partial \ln w_x}, \tag{11}$$

or

$$\mathbf{0} = \mu \mathbf{c}^L + \frac{\mu}{1-\sigma} \mathbf{B}^L \mathbf{J}^L \tag{12}$$

in matrix notation. We solve (12) for $\mathbf{J}^L$, which yields $\mathbf{J}^L = (\sigma - 1)\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L$, and substitute this into (8) and (10). The term c^L_{rx} ($c^L_{rx} \lesseqgtr 0$) reflects the extent to which a wage shock in region x distorts equality of the real wage rates between region r and an arbitrarily chosen reference region at a given regional distribution of employment. c^L_{rx} is positive, if the real wage rate in r drops below that in the reference region. The wage rate in r drops below that in the reference region, if the wage-induced price effect (see 9) induced by the wage shock in x raises the CPI in r by more than that in the reference region, that is, if the the consumers in r buy more extensively from x than those in the reference region. The wage shock itself reduces this effect, if it hits r itself, and adds to this effect, if it hits the reference region. The term $\sum_{s=1}^{R} b^L_{rs}\frac{\partial \ln L^M_s}{\partial \ln w_x}$ reflects the effects of migration needed to restore real wage equalization between r and the reference region. If a wage shock in region x raises the CPI in r by more than that in the reference region, such that $c^L_{rx} > 0$, the migration-induced price effect (see 9), must reduce the CPI in r by more than that in the reference region through the competition effect in order to restore real wage equalization. More workers must, ceteris paribus, migrate to r or its main suppliers than to the reference region or its main suppliers.

In summary, after having eliminated all endogenous variables, we can express the bilateral regional elasticities of wages as

$$\mathbf{J}^w = \frac{1}{\sigma}\left[\mathbf{f}^y + (\sigma-1)\,\mathbf{f}^y\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L + \mathbf{f}^g\left(\mathbf{c}^g + \mathbf{c}^g\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L\right)\right]. \qquad (13)$$

After extracting $\frac{1}{\sigma}$, which we will estimate by the regressions, out of the matrix $\mathbf{J}^w$ and adding an error term, $\boldsymbol{\varepsilon}$, which accounts for random shocks and Taylor approximation errors, the empirical SAR(1) model to be estimated becomes

$$\ln \mathbf{w} - \ln \widetilde{\mathbf{w}} = \frac{1}{\sigma}\left[\mathbf{W}\left(\sigma, \mu, \mathbf{T}, \mathbf{L}^A, \widetilde{\mathbf{w}}, \widetilde{\mathbf{L}^M}\right)\right](\ln \mathbf{w} - \ln \widetilde{\mathbf{w}}) + \boldsymbol{\varepsilon}, \qquad (14)$$

where

$$\mathbf{W} := \sigma \mathbf{J}^w = \mathbf{f}^y + (\sigma-1)\,\mathbf{f}^y\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L + \mathbf{f}^g\mathbf{c}^g + \mathbf{f}^g\mathbf{c}^g\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L \qquad (15)$$

is the spatial weights matrix that reflects the extent to which, according to the NEG model, the regional wage rates are related to each other. It summarizes all four effects introduced before, the "wage-induced income effect" (matrix $\mathbf{f}^y$), the "migration-induced income effect" (matrix $(\sigma-1)\,\mathbf{f}^y\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L$), the "wage-induced price effect" (matrix $\mathbf{f}^g\mathbf{c}^g$), and the "migration-induced price effect" (matrix $\mathbf{f}^g\mathbf{c}^g\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L$). This matrix can be calculated for any set of predetermined structural parameters of the NEG model, the values of the exogenous variables, and the equilibrium values of the regional wages and employment quantities. Having parameterized the spatial weights, we can estimate $\frac{1}{\sigma}$ from (14). If this estimate is equal to the inverse of the predetermined substitution elasticity used to calculate $\mathbf{W}$, we will conclude that the corresponding set of predetermined structural parameters solves the general equilibrium of the NEG model, and interpret the regression fit as an indicator of how well the NEG model fits the data, i.e., to what extent regional wages do in fact respond to local wage shocks in the way predicted by the NEG model.

Our empirical model (14) differs in several respects from the models used in regression-based tests of nonlinear NEG models. First, it brings a whole NEG model consistently to the data. Unlike the models estimated in Hanson (2005) and Mion (2004), it takes explicitly into account the definition of the CPI and the labor market equilibrium, and thereby the rich variety of *inter*dependencies between wages, demand, consumer prices, and migration. And unlike the model estimated in Redding and Venables (2004), it consistently takes into account all parameter restrictions implied by the NEG model.[10] Second, it possibly incurs a smaller Taylor approximation error as models that used Taylor approximation for linearizing wage equations before. Combes and Lafourcade (2008) and Mion (2004) approximate the (logged) wage equation at a perfect-integration equilibrium of the NEG model with zero interregional transport costs while they assume the observed regional distribution of wages to be shaped by positive interregional transport costs. We avoid this wedge between equilibrium and disequilibrium transport costs. Third, it takes a region's own contribution to its market potential explicitly into account. In virtually all models estimated in earlier regression-based studies,[11] aggregate demand for goods produced in the home region is set to zero to reduce endogeneity problems. Fourth, it derives "instruments" for endogenous right-hand side variables of the wage equation right from the theoretical model, rather than specifying them outside the model in a rather ad hoc fashion. This largely reduces problems arising from weak instruments. Since the spatial lag of the wage shocks, $\mathbf{W}(\ln \mathbf{w} - \ln \widetilde{\mathbf{w}})$ in (14), must be considered endogenous, our model is not entirely immune against endogeneity problems, though. And finally, it facilitates test of selected elements of the NEG model separately. These elements as well as the way they are tested will be discussed in the next subsection.

3.2 Model components

The SAR(1) model (14) with spatial weights (15) represents the full Krugman-type NEG model as closely as possible. It features simultaneously all four effects introduced in the previous subsection, the wage- and migration-induced income effects and the wage- and migration-induced price effects. We will henceforth

[10] Redding and Venables (2004) estimate two equations successively, a trade and a wage equation. They use the results of the estimation of the trade equation, which does not take parameter restrictions into account, to determine the real market potential, which is then plugged into the wage equation. They then estimate the wage equation to obtain an estimate the substitution elasticity.

[11] These studies include Hanson (2005), Mion (2004), and Redding and Venables (2004). Head and Mayer (2006) is an exception.

refer to this model as model 0, or the "full" model, and denote the corresponding spatial weights matrix (15) by $\mathbf{W}_0$,

$$\mathbf{W}_0 = \mathbf{f}^y + (\sigma - 1)\,\mathbf{f}^y \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L + \mathbf{f}^g \mathbf{c}^g + \mathbf{f}^g \mathbf{c}^g \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L. \tag{16}$$

The empirical results obtained from estimating this full model will be indicative of how well the NEG model as a whole fits the data.

In addition to the full model, we derive four empirical models that feature only subsets of the four effects introduced in the previous subsection by imposing restrictions on endogenous variables of the NEG model. The resulting empirical models differ from the full model only in the spatial weights matrices. Like the full model, they are SAR(1) models and can thus be estimated in exactly the same way.

1. The first restriction imposed on the full model is assuming all consumer prices, and thus the consumer price indices in all regions, to be exogenous and fixed at their equilibrium values. This restriction is equivalent to "switching off" the wage- and the migration-induced price effects introduced in the previous subsection by setting $\frac{\partial \ln g_r}{\partial \ln w_x} = 0 \ \forall \ r, x = 1, ..., R$. Under this assumption, producers of manufacturing goods cannot adjust their sales prices to changes in wages. The wage- and the migration-induced income effects do still work, though. With $\frac{\partial \ln g_r}{\partial \ln w_x} = 0$, the spatial weights matrix (15) simplifies to

   $$\mathbf{W}_1 = \mathbf{f}^y + (\sigma - 1)\,\mathbf{f}^y \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L. \tag{17}$$

   The SAR(1) model with $\mathbf{W} = \mathbf{W}_1$ will be labeled model 1. $\mathbf{W}_1$ represents a partial equilibrium of the NEG model in the presence of fixed prices but regionally mobile labor. By comparing the empirical performance of this model 1 to that of model 0, we will assess whether or not the data support the wage- and migration-induced price effects predicted by the NEG model when labor is mobile.

2. The second restriction imposed on the full model is assuming manufacturing employment in all regions to be exogenous and fixed at their equilibrium values. This restriction is equivalent to switching off the two migration-induced effects by setting $\frac{\partial \ln L_r^M}{\partial \ln w_x} = 0 \ \forall \ \ r, x = 1, ..., R$. Under this assumption, real wage differences between regions do not induce any migration of manufacturing workers. The wage-induced income and price effects do still work, though. With $\frac{\partial \ln L_r^M}{\partial \ln w_x} = 0$, the spatial weights matrix (15) simplifies to

   $$\mathbf{W}_2 = \mathbf{f}^y + \mathbf{f}^g \mathbf{c}^g. \tag{18}$$

   The empirical model (14) with $\mathbf{W} = \mathbf{W}_2$ will be labeled model 2. $\mathbf{W}_2$ represents a general equilibrium of the NEG model in the presence of immobile labor but flexible prices. By comparing the empirical performance of this model 2 to that of model 0, we will assess whether or not the data support the two migration effects predicted by the NEG model.

3. The third restriction imposed on the full model is assuming both consumer price indices, and manufacturing employment to be exogenous and fixed ($\frac{\partial \ln g_r}{\partial \ln w_x} = \frac{\partial \ln L_r^M}{\partial \ln w_x} = 0 \; \forall \; r, x = 1, ..., R$). Under this assumption, only the wage-induced income effect is still working. The spatial weights matrix (15) simplifies to

$$\mathbf{W}_3 = \mathbf{f}^y. \tag{19}$$

The empirical model (14) with $\mathbf{W} = \mathbf{W}_3$ will be labeled model 3. It represents a partial equilibrium of the NEG model in the presence of immobile labor and fixed prices. By comparing the empirical performance of this model 3 to those of models 1 and 2, we will assess whether or not the data support the migration-induced income effect predicted by the NEG model when prices are fixed, and the two price index effects when labor is immobile.

4. Finally, the fourth restriction is eliminating all effects featured by the NEG model from the empirical model and instead conditioning the spatial weights on geographic distances only. We impose this restriction by setting

$$\mathbf{W}_4 = \mathbf{T}, \tag{20}$$

where the $(R \times R)$ matrix $\mathbf{T}$ is the matrix of interregional transport costs (T_{rs}). The empirical model (14) with $\mathbf{W} = \mathbf{W}_4$ will be labeled model 4. This model is theoryless. It is not informative about economic forces shaping the regional distribution of wages. Notice that all main diagonal elements of $\mathbf{W}_4$ are zero because intraregional transport costs are assumed to be zero in the NEG model, while the main diagonal elements of the other weights matrices, $\mathbf{W}_0, ..., \mathbf{W}_3$ are non-zero. By comparing the empirical performance of this model 4 to those of models 0 through 3, we will assess whether or not the data support the wage-induced income effects predicted by the NEG model individually, or jointly with price index or migration-induced effects.

Table 1 gives an impression of the magnitudes of the bilateral wage elasticities in the spatial weights matrices $\mathbf{W}_0 - \mathbf{W}_4$, calculated for values of the structural parameters that are close to those estimated in the regressions below. It shows that, according to the NEG model, regional wages may respond very sensitively to local wage shocks when labor is assumed to be mobile (models 0 and 1). This is true for the responses to both a wage shock within the same region (rows labeled "intra") as well as a wage shock in another region ("inter").

Model 0, for example, predicts a region's own wage rate to ultimately decrease by up to 12.21% or to increase by up to 1.889% in response to a 1% wage shock in this region. And it predicts the wage rates in other regions to change by between –5.271% and +5.59%. The magnitudes of the effects of wage shocks are more moderate in models 2 and 3 where labor is assumed to be immobile. They are, still, higher if prices are assumed to be flexible (model 2) than if they are assumed to be fixed (model 3). In addition to being more moderate, the effects of wage shocks are non-negative for all pairs of regions in models 2 and 3. Since reallocation of resources is not allowed in models 2 and 3, local wage shocks in any directions must induce nominal wages elsewhere to change in the same direction. These induced changes in nominal wages will be higher, if firms are allowed to adjust their prices to the higher production costs (model 2).

Table 1. Descriptive statistics for bilateral regional wage elasticities in models $0-4$

Model	Scope	Mean	Std.dev	Min	Max
0	intra	-0.515	0.885	-12.21	1.889
0	inter	0.000	0.02	-5.271	5.590
1	intra	-0.889	0.810	-12.35	1.731
1	inter	0.000	0.018	-5.629	5.519
2	intra	0.142	0.173	0.001	0.939
2	inter	0.000	0.005	0.000	0.632
3	intra	0.051	0.045	0.001	0.258
3	inter	0.000	0.001	0.000	0.140
4	intra	0	0	0	0
4	inter	0.01	0.04	0.00	0.92

Notes: Rows labeled "intra" report statistics for all 3,076 main diagonal elements ($\sigma\frac{\partial \ln w_r}{\partial \ln w_x}$, $x = r$) of the corresponding spatial weights matrices $\mathbf{W}_0 - \mathbf{W}_4$ (equations 16–19), rows labeled "inter", for all 9,458,700 off-diagonal elements ($\sigma\frac{\partial \ln w_r}{\partial \ln w_x}$, $x \neq r$) of the respective spatial weights matrices. All elements of the spatial weights matrices derived from the NEG model ($\mathbf{W}_0 - \mathbf{W}_3$) are divided by σ (see equation 15 in section 3.1). The structural parameters used for calculating these matrices are: $\sigma = 3.5$, $\tau = 0.02$ (0.0199 for model 4), $\mu = 0.5$.

The figures in Table 1 clarify that the full effects of wage shocks can hardly be expected to materialize within a single year, which is the length of one time period in our empirical investigation below. We do, in fact, not find equilibria of the NEG models represented by the full matrices $\mathbf{W}_0$, $\mathbf{W}_1$, and $\mathbf{W}_2$ in our empirical investigation. This is possibly due to the fact that migration and price adjustments, which are assumed to be cost- and frictionless in the model, are subject to—in some cases—significant costs and frictions in practice. Only a small fraction of the total net migration flows and price adjustments predicted by the theoretical model may thus actually materialize within a single year. We will therefore abstract in our empirical tests from the *absolute* magnitudes of the predicted wage elasticities between regions and focus instead on the directions and relative magnitudes of these elasticities. We do this by introducing additional sluggishness parameters ϕ_j $(0 \leq \phi_j \leq 1)$ for all responses of wages predicted by the model that involve price adjustments and/or migration. While we assume that the wage-induced income effects, featured by model 3, do fully materialize within one year, we allow the wage-induced price effects and the two migration-induced effects to materialize only partially by a percentage that we restrict to be the same for all pairs of regions.[12] More specifically, we modify the spatial weights $\mathbf{W}_0 - \mathbf{W}_2$ (equations 16 to 18) in the following way:

$$\mathbf{W}_{2,\phi_2} = \mathbf{f}^y + \phi_2 \mathbf{f}^g \mathbf{c}^g, \tag{21}$$

$$\mathbf{W}_{1,\phi_1} = \mathbf{f}^y + \phi_1 (\sigma - 1) \mathbf{f}^y \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L, \tag{22}$$

$$\mathbf{W}_{0,\phi_0} = \mathbf{f}^y + \phi_0 \left((\sigma - 1) \mathbf{f}^y \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L + \mathbf{f}^g \mathbf{c}^g + \mathbf{f}^g \mathbf{c}^g \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L\right). \tag{23}$$

The sluggishness parameter ϕ_2 scales down the wage-induced price effects vis-a-vis the wage-induced income effects in model 2, the parameter ϕ_1 the migration-induced income effects vis-a-vis the wage-induced income effects in model 1, and the parameter ϕ_0 the combined migration-induced income and price effects as well as the wage-induced price effects vis-a-vis the wage-induced income effects in model 0. $\phi_j = 1$ $(j = 0, 1, 2)$ implies that the respective price or migration effects materialize to the full extent. Equations (21) – (23) are equal to equations (16) – (18) in this case. $\phi_j = 0$ implies that the respective price or migration effects do not materialize at all within one year. Models 0, 1 or 2 reduce to model 3 in this case. And $0 < \phi_j < 1$ implies that only a fraction of the full price effects or migration flows predicted by the model actually materialize within one year.

To sum up, we expect that the models that feature mobile labor (models 0 and 1) will fit the data better than the corresponding models that feature immobile labor (models 2 and 3) for at least one positive value of ϕ_0 and ϕ_1, respectively, if the NEG model gets the incentives for, and the consequences of migration right. By the same token, we expect that the models that feature flexible prices (models 0 and 2) will fit the data better than the corresponding models that feature constant prices (models 1 and 3) for at least one positive value of ϕ_0 and ϕ_2, respectively, if the NEG model gets the incentives for, and the consequences of price adjustments right.

4 Estimation method and data

This section discusses details of specification and estimation of our five SAR(1) models 0–4 just introduced.

[12] This kind of modeling the ad doc dynamics of price or migration adjustments is conceptually fairly similar to that in Fujita et al. (1999: 62).

4.1 Empirical model

The basic equation to be estimated is based on (14), which is a SAR(1) model in the deviations of regional wages from their equilibrium values:

$$u_{rt} = \rho \sum_{x=1}^{R} \omega_{rx} u_{xt} + \varepsilon_{rt}, \tag{24}$$

where

$$\begin{aligned} u_{rt} &= \ln w_{rt} - \ln \widetilde{w}_r, \\ \omega_{rx} &= \sigma \frac{\partial \ln w_r}{\partial \ln w_x} \left(\widetilde{\mathbf{w}}, \widetilde{\mathbf{L}}^M, \mathbf{L}^A, \mathbf{T}, \sigma, \mu \right), \\ \rho &= 1/\sigma. \end{aligned} \tag{25}$$

The spatial weights, ω_{rx}, are given by the elements of one of the five spatial weights matrices introduced in the previous section. For the models 0–3, the equilibrium values of the endogenous variables of the theoretical model that enter the spatial weights, $\ln \widetilde{\mathbf{w}}$ and $\widetilde{\mathbf{L}^M}$, must be treated as exogenous variables. Following the literature, we approximate them by their long-run averages over the sample period, i.e., by $\ln \widetilde{\mathbf{w}} = \frac{1}{T} \Sigma_{t=1}^{T} \ln \mathbf{w}_t$ and $\widetilde{\mathbf{L}^M} = \frac{1}{T} \Sigma_{t=1}^{T} \mathbf{L}_t^M$.[13] For model 4, the spatial weights depend only on geographical distances, which we assume to be exogenous. The iceberg transport costs, $\mathbf{T}$, are one for intraregional trade and increase with increasing interregional distance in the theoretical model. We specify them in terms of exponential distances, such that the transport costs between any two regions r and s are given by $T_{rs} = \exp(\tau D_{rs})$. The distance decay parameter τ determines the percentage of the iceberg's actual size that melts away during one additional mile. In contrast to most of the empirical literature, we prefer the exponential over the power function (D_{rs}^{τ}) because the latter is inconsistent with the iceberg concept. The power function converges to infinity rather than to one with decreasing distance.

We modify the empirical model (24) in two respects in order to account for real world imperfections: First, we eliminate time-varying country-wide wage shocks by subtracting the time-specific national averages, $\frac{1}{R} \sum_{q=1}^{R} \ln w_{qt}$, from all regional wage rates. Notice that the variables in (24) are already net of time-invariant region-specific effects *by construction.* Taken together, we follow Baltagi (1995: 28) in that we within-transform regional wages by replacing $\ln \widetilde{w}_r$ in (25) with $\ln \widetilde{w}_{rt}$

$$\ln \widetilde{w}_{rt} = \frac{1}{T} \sum_{s=1}^{T} \ln w_{rs} + \frac{1}{R} \sum_{q=1}^{R} \ln w_{qt} - \frac{1}{RT} \sum_{q=1}^{R} \sum_{s=1}^{T} \ln w_{qs}.$$

[13] This assumption is not unproblematic because any shock may affect the equilibrium permanently. We still stick to this simplifying assumption because the properties of estimators for spatial lag models like our SAR(1) model with endogenous spatial weights are still unknown. This assumption may be relaxed in the future if a consistent estimator for spatial lag models with endogenous spatial weights is available.

Second, following Mion (2004) and Head and Mayer (2006), who show that wage shocks usually do not exhaust within a single year, we allow for sluggishness in wage adjustments by estimating a dynamic version of (24). Adding the serial lag of the dependent variable, u_{rt-1}, to our basic model (24), we interpret our reduced-form wage equation as determining the equilibrium levels of regional wages in year t to which the observed levels adjust only partially during the year of a shock. (24) consequently becomes

$$u_{rt} = (1-\theta)\,\rho \sum_{x=1}^{R} \omega_{rx} u_{xt} + \theta u_{rt-1} + \varepsilon_{rt}, \tag{26}$$

where u_{rt} is a within-transformed logged regional wage rate, and θ $(0 \leq \theta \leq 1)$ a measure of the sluggishness of wage adjustments to be estimated. Stacking (26) over regions for each time period gives, in matrix notation,

$$\mathbf{u}_t = (1-\theta)\,\rho \mathbf{W} \mathbf{u}_t + \theta \mathbf{u}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{27}$$

which is the model estimated in this paper for all spatial weights matrices, using data for a panel of U.S. counties for the period 1990–2005.

The NEG model does not account for regional differences in human capital intensities. It assumes labor to be homogeneous. In practice, however, both the average skill level of workers and the market potential tend to be higher in metropolitan areas. Even though the within transformation of the wages and the serial lag of the dependent variable can be expected to eliminate much of the skill premia embodied in regional wages, the spatial-lag parameter ρ in (27) may still be subject to an omitted variable bias. An obstacle to controlling effectively for skill premia in the present paper is the lack of reliable data, however.[14] We therefore assume—and verify in Appendix 2 with own estimates of human-capital intensities—that time-varying regional differences in human capital intensities do not affect our main results. This assumption is broadly in line with Head and Mayer (2006) who show for Europe that the effect of the RMP on regional wages is still significant after controlling for regional differences in educational attainment.

4.2 Estimation strategy

Three issues need to be dealt with when estimating the SAR(1) model (27) for our five spatial weights matrices: endogeneity, identification of the parameters, and model evaluation. As to endogeneity of regressors, we assume that the serially lagged dependent variable, $\mathbf{u}_{t-1}$, is exogenous. Since region specific effects

[14] Data on educational attainment of the regional workforces is not available at all at the county level, and data on educational attainment of the working-age population is available only from the decennial censuses in 1990 and 2000.

are already eliminated by construction from the model, there is no need to take first differences of (27) that would make the serial lag endogenous. The spatially lagged dependent variable, $\mathbf{W}\mathbf{u}_t$, is endogenous and should be instrumented, by contrast. Since (27) contains region and time varying explanatory variables, and since the serial lag is assumed to be exogenous, we can construct instruments for the spatial lag by solving (27) for $\mathbf{u}_t$. This gives, under the usual regularity conditions,

$$\begin{aligned}\mathbf{u}_t &= (\mathbf{I}_R - (1-\theta)\,\rho\mathbf{W})^{-1}\,[\theta\mathbf{u}_{t-1} + \boldsymbol{\varepsilon}_t] \\ &= \sum_{m=0}^{\infty}[(1-\theta)\,\rho\mathbf{W}]^m\,[\theta\mathbf{u}_{t-1} + \boldsymbol{\varepsilon}_t]\,. \end{aligned} \tag{28}$$

$\mathbf{I}_R$ is an $(R \times R)$ identity matrix. Possible instruments for the spatial lag of the dependent variable thus include $\mathbf{W}^m\mathbf{u}_{t-1}$ $(m > 0)$, which are the first and higher-order spatial lags of the serial lag $\mathbf{u}_{t-1}$. We use the first two spatial lags, $\mathbf{W}\mathbf{u}_{t-1}$ and $\mathbf{W}^2\mathbf{u}_{t-1}$, and additionally their serial lags up to $\mathbf{W}\mathbf{u}_{t-4}$ and $\mathbf{W}^2\mathbf{u}_{t-4}$ as GMM-type instruments. Moreover, we use the exogenous variable $\mathbf{u}_{t-1}$ as an additional instrument.

As to identification of parameters, the theoryless model 4 has three parameters: the transport cost parameter, τ, the partial adjustment parameter, θ, and the spatial lag parameter ρ, which is not related to the substitution elasticity. We perform a line search over plausible transport cost parameters in order to find the value of τ that fits the data best, according to the R^2. The four NEG-based models with spatial weights $\mathbf{W}_0 - \mathbf{W}_3$ comprise four parameters. In addition, the models with spatial weights $\mathbf{W}_0 - \mathbf{W}_2$ comprise one sluggishness parameter ϕ_j $(j = 0, 1, 2)$ each. Three parameters, the substitution elasticity, σ, the transport cost parameter, τ, and the expenditure share for manufacturing goods, μ, are from the theoretical model, and must be determined prior to the estimations to calculate the spatial weights. The substitution elasticity enters the model as both an exogenous constant in the spatial weights and as a parameter to be estimated $(\sigma = 1/\rho)$. The fourth parameter is the partial adjustment parameter, θ. Even though it would be preferable to estimate all these parameters simultaneously, this is unfortunately not feasible. If, for example, the parameters τ and σ would be estimated simultaneously by unconstrained least squares (or maximum likelihood), the sum of squared residuals were always minimal (or the likelihood would always be maximal) for $\tau(1-\sigma) = -\infty$, i.e., for autarchy of all regions. The spatial weights matrix degenerated to $\sigma\mathbf{I}_R$ in this case, and the regions' wages were actually explained perfectly by themselves.

To keep the estimations of the four NEG-based models tractable, we estimate only two parameters, σ and θ, while we set τ and μ exogenously and determine ϕ_j by a grid search. We set $\tau = 0.02$ and $\mu = 0.5$, and assume both parameters to be constant over time. The transport cost parameter of $\tau = 0.02$ is very close to the value estimated for the distance decay parameter in the theoryless model 4 (0.0199, see below). It implies that 80% of the ice-berg is gone after 80 miles, 86,5% after 100 miles, and 98.2% after 200 miles. Sensitivity tests indicate that our main results do not depend crucially on the choice of the transport cost parameter (Appendix 2). The expenditure share of $\mu = 0.5$ is approximately equal to the average annual expenditures on food (1992: 14.3%), alcoholic beverages (1%), housing (31.8%), education (1.4%) and tobacco products and smoking supplies (0.9%) in the U.S. in the period under study.[15] Given this choice of the expenditure share, all values of $\sigma > 2$ meet the no black hole condition, $\sigma(1-\mu) > 1$ (see Fujita et al. 1999:59), which ensures that the elasticity of wages with respect to employment is negative in the NEG models that feature mobile labor. Finally, we assume the agricultural sector in the theoretical model to comprise agriculture, mining, construction, education and health services, and public administration. These five industries account for about 30% of the long-run average employment in the U.S.

To identify σ, we have to equate the estimated value of σ, henceforth denoted $\widehat{\sigma}\,(=1/\widehat{\rho})$, to the predetermined value in the spatial weights matrix, henceforth denoted $\overline{\sigma}$. Since such a fixed-point cannot be taken for granted (see Appendix 2), and since we need to ensure that an existing fixed point is unique, we follow Fingleton (2006) in performing a grid search over plausible values of σ. We first calculate various spatial weights matrices for a grid of predetermined $\overline{\sigma}$, and estimate a $\widehat{\sigma}$ for each of the corresponding spatial weights matrices. We then perform a line search between the two grid points with minimal distances $|\widehat{\sigma} - \overline{\sigma}|$ to identify the fixed-point. We subject a fixed-point to two convergence criteria:

1. $|\widehat{\sigma} - \overline{\sigma}| < 0.01$, i.e., the difference between predetermined and estimated values of σ must be sufficiently small in absolute terms, and

2. $|prob\,(\sigma < \overline{\sigma}) - 0.5| < 0.01$, i.e., the probability that the estimated value of σ differs from its predetermined value must be sufficiently small.

To identify the sluggishness parameters, ϕ_j $(j = 0, 1, 2)$, for migration and price adjustments, we determine the values of ϕ_j by a manual grid search. For reasons the become obvious below, we report in Section 5 the results of the estimations for the highest value of ϕ_j that supports a fix point for a plausible value of σ.

As to model evaluation, we compare the five SAR(1) models by means of their R^2s.[16] We also compared the models by means of spatial J tests (Kelejian 2008). These tests, the results of which are not reported here, yield inconclusive results for most of the pairs of our SAR(1) models, however. Monte Carlo

[15] See Bureau of Labor Satatistics, Consumer Expenditure Survey, Shares of average annual expenditures and sources of income, 1992, available at http://www.bls.gov/cex/csxshare.htm.

[16] We add a constant term to our regression model to calculate the R^2 in the conventional way. This constant term is small and insignificant in all regressions.

simulations by Piras and Lozano-Gracia (2010) indicate that the power of the spatial J test may be rather low for low values of the spatial lag parameters. Model evaluation may be subjected to formal testing in the future, if powerful test statistics for discriminating between different spatial weights matrices in spatial autoregressive models are available.

4.3 Data

We use annual data on 3,076 counties in the 48 mainland US states and Washington, DC., for the period 1990–2005. The regional wage rates, w_{rt}, are calculated as (nominal) wage and salary disbursements divided by wage and salary employment (number of jobs). The data is available from the Regional Economic Information System (REIS, Table CA34) of the Bureau of Economic Analysis (BEA). Wage and salary disbursements measures the remuneration of employees and includes the compensation of corporate officers, commissions, tips, bonuses, and pay–in–kind. It accounted for 57% of total personal income at the national level in 2001, according to BEA. Wage and salary employment measures the average annual number of full-time and part-time jobs by place-of-work. Full-time and part-time jobs are counted with equal weight. We do not deflate the nominal wage rates, or exclude wage and salary disbursements in agriculture.

We measure employment in the increasing-returns industry, L_r^M, by total regional wage and salary employment minus agricultural employment, L_r^A, and agricultural employment by annual average employment in Natural Resources and Mining (NAICS 2002: 1011), Construction (1012), Education and Health Services (1025) and Public Administration (1028) reported by the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). These sectors account for about 30% of the long-run average employment in the U.S. To reduce the effects of mismatches between the BEA and QCEW data, we calculate employment in the increasing-returns industry as $L_r^M = \left(1 - l_{r,QCEW}^A\right) L_{r,BEA}$, where $L_{r,BEA}$ denotes total wage and salary employment in region r from BEA, and $l_{r,QCEW,}^A$ the share of our agricultural sector in total employment from the QCEW. Finally, we calculate the distances between counties as great circle distances between the counties' centroids. The coordinates of the counties' centroids are from Rick King's dataset at http://home.comcast.net/~rickking04/gis/spcmeta. htm.

5 Results

This section presents and discusses the results of the nonlinear 2SLS regressions for the SAR(1) model (27) with the spatial weights matrices given in equations (19)–(23).[17] Table 2 summarizes these results. All results refer to equilibrium solutions of the underlying NEG models. We identify these equilibria by equality

[17] The data and the SAS code are available at http://hdl.handle.net/1902.1/14189.

of the predetermined and estimated values of the substitution elasticity ($\widehat{\sigma} = \overline{\sigma}$). The upper panel of Table 2 reports the characteristics of the NEG models from which the spatial weights are derived. The middle panel reports the values of the predetermined structural parameters of the corresponding NEG model used to calculate the spatial weights, including the values of the sluggishness parameters ϕ_j. The lower panel, finally, reports the estimated regression parameters, the regression fit statistic, R^2, and the R^2 of the first-stage regression (1^{st}st.R^2). Complementing the information in Table 2, Table 3 depicts descriptive statistics for the bilateral regional wage elasticities, $\frac{\partial \ln w_r}{\partial \ln w_x}$, implied by the estimation results. Table 3 has the same shape as Table 1 in Section 3.2.

Table 2. Regression results for models 0 – 4

Model	0	1	2	3	4
Model elements					
wage-induced income effect	✓	✓	✓	✓	
wage-induced price effect	✓		✓		
migration-induced income effect	✓	✓			
migration-induced price effect	✓				
Predetermined parameters in spatial weights					
σ (substitution elasticity)	3.5	3.52	3.75	1.751	—
τ (transport costs)	0.02	0.02	0.02	0.02	0.0199
μ (expend. share manuf.)	0.5	0.5	0.5	0.5	—
ϕ (sluggishness discount)	0.0646	0.05389	0.582	1	—
Estimated parameters					
σ (substitution elasticity)	3.500	3.520	3.751	1.751	0.031[a]
(std.dev.)	(0.36)	(0.40)	(0.17)	(0.14)	(0.002)
θ (partial adjustment)	0.748	0.752	0.714	0.742	0.737
(std.dev.)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
R^2	0.580	0.578	0.611	0.588	0.590
First stage R^2	0.678	0.700	0.746	0.816	0.773

[a] Parameter ρ.

Notes: Nonlinear 2SLS regressions of SAR(1) model (27) with spatial weights $\mathbf{W}_{0,\phi_0}$ (equation 23), $\mathbf{W}_{1,\phi_1}$ (22), $\mathbf{W}_{2,\phi_2}$ (21), $\mathbf{W}_3$ (19), or $\mathbf{W}_4$ (20) for 3076 U.S. counties 1990–2005 (46,140 observations).

Table 3. Descriptive statistics for estimated bilateral regional wage elasticities in models 0 – 4

Model	σ	ϕ	Scope	Mean	Std.dev	Min	Max
0	3.5	0.065	intra	0.014	0.082	-0.764	0.290
0	3.5	0.065	inter	0.000	0.002	-0.298	0.371
1	3.52	0.054	intra	0.000	0.061	-0.646	0.204
1	3.52	0.054	inter	0.000	0.001	-0.249	0.310
2	3.75	0.582	intra	0.120	0.127	0.001	0.645
2	3.75	0.582	inter	0.000	0.003	0.000	0.416
3	1.751	—	intra	0.014	0.031	0.000	0.338
3	1.751	—	inter	0.000	0.002	0.000	0.237
4	—	—	intra	0	0	0	0
4	—	—	inter	0.000	0.001	0.000	0.028

Notes: Rows labeled "intra" report statistics for all 3,076 main diagonal elements ($\sigma\frac{\partial \ln w_r}{\partial \ln w_x}$, $x = r$) of the spatial weights matrices $\mathbf{W}_{0,\phi_0}$ (equation 23), $\mathbf{W}_{1,\phi_1}$ (22), $\mathbf{W}_{2,\phi_2}$ (21), $\mathbf{W}_3$ (19), or $\mathbf{W}_4$ (20), calculated for the respective parameters depicted in Table 2, rows labeled "inter", for all 9,458,700 off-diagonal elements ($\sigma\frac{\partial \ln w_r}{\partial \ln w_x}$, $x \neq r$) of the respective spatial weights matrices. All elements of the four spatial weights matrices derived from the NEG model ($\mathbf{W}_0 - \mathbf{W}_3$) are multiplied by σ.

For model 0, which represents the full NEG model featuring mobile labor and flexible prices, we find that fixed points for σ exist for sluggishness parameters of $\phi_0 \leq 0.065$. All specifications of this model where the sluggishness parameter is assumed to be below this threshold have a fixed point while all specifications where it is above this threshold have not. This implies that we succeed in fitting the full NEG model to U.S. data as long as we assume that no more than 6.5% of the total migration needed to restore equilibrium after a wage shock take place in the same year as the shock. This percentage is fairly high in the light of the fact that migration is usually subject to significant costs and frictions. It is, however, not implausibly high in the light of the fact that workers are fairly mobile in the U.S. The descriptive statistics for the wage elasticities implied by the fitted model 0 (first two rows in Table 3) indicate that the sluggishness parameter downscales the intra- and interregional wage elasticities to plausible magnitudes. While the long-term elasticities, which characterize the total adjustment needed to restore equilibrium, range from -12 to $+5.6$ (see Table 1), the short-term elasticities in our regrssions do not exceed one in absolute terms for any pair of counties. The statistics also indicate that the multiregion NEG model predicts regions to be affected by local wage shocks rather heterogeneously. While some regions experience an increase of their wage rate after being exposed to a positive wage shock, others experience a decrease.[18] The estimated parameters, depicted in the lower panel of Table 2,

[18] On top of the ranking of the short-term intraregional elasticities are large, prosperous metropolitan centers like Clark, Nevada (Las Vegas), Los Angeles, San Diego, and Orange, California, or Harris, Texas (Houston).

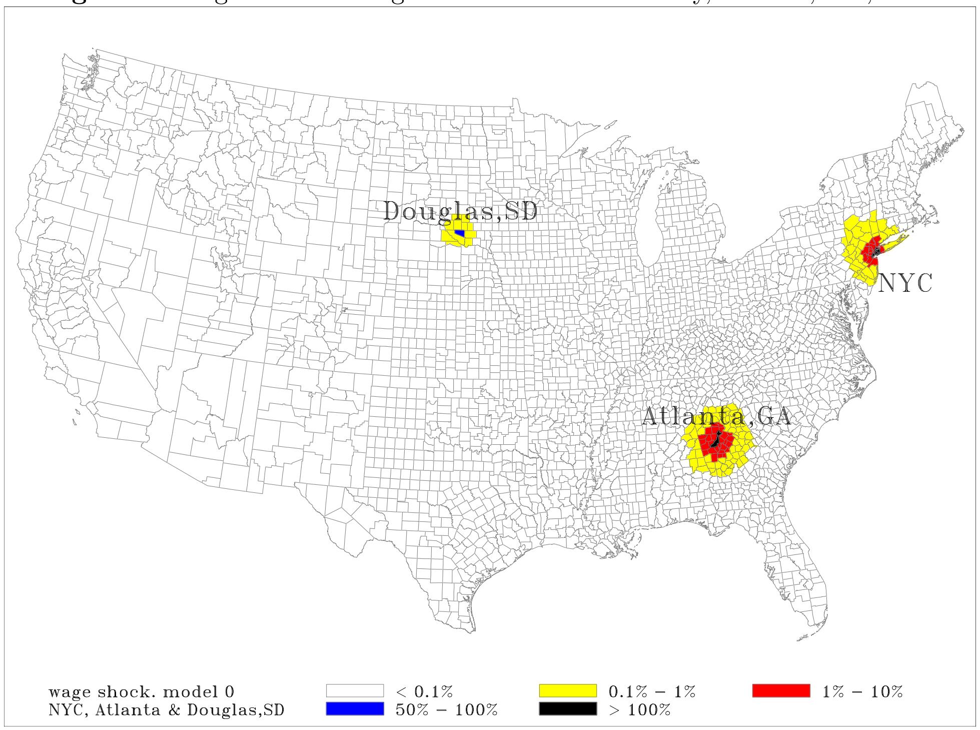
are statistically significant and of plausible magnitudes. The partial adjustment parameter, θ, is estimated to be around 3/4, which implies that, on average, about 1/4 of a wage shock is worked off within one year, and is available for being explained by the NEG model in our specifications. The substitution elasticity, σ, our parameter of main interest, is estimated to be 3.5, which is well within the range of estimates for σ found in the literature (Head and Ries 2001).

A simulation exercise shows that the model predicts the short-term wage effects of shocks to attenuate continuously and fairly rapidly with increasing distance to the origin of the shock (Figure 1). We simulate the direct and indirect (multiplier) effects of a wage shock of arbitrary magnitude in three selected regions, New York City (NYC), Atlanta, GA (Fulton county), and Douglas county, SD, on the nominal wages in all regions.[19] The model predicts a wage shock in all five counties of NYC to raise wage rates in NYC itself by between 100%–102% of the initial shock, and those in counties neighboring NYC by up to 2% of the shock. The wage shock in Atlanta, GA, is predicted to raise the wage rate in Atlanta by about the same magnitude, and to also attenuate fairly rapidly with increasing distance to Atlanta. The wage shock in rural Douglas, SD, has similar but smaller effects.

The NEG model predicts that all three regions exposed to the shock loose employment while their neighboring regions gain employment. By raising production costs and thus the prices of the traded varieties, the shock weakens the competitiveness of the firms in the regions exposed to the shock considerably. Consumers reorganize their consumption bundles in order to escape the higher prices for the varieties from these regions. As a consequence, firms from these regions move to neighboring regions where wages are lower to escape the increased competitive pressure. And workers from these regions move to neighboring regions where the prices for locally produced varieties are lower.

[19] These predicted wage effects, denoted by $\widehat{\mathbf{u}}$, are calculated as $\widehat{\mathbf{u}} = 100 \left(\mathbf{I}_R - \frac{1-\widehat{\theta}}{\widehat{\sigma}} \mathbf{W} \right)^{-1} \mathbf{q}$, using the parameter estimates depicted in Table 2. $\mathbf{q}$ denotes an $(R \times 1)$ vector of shocks whose entries are 1 for the regions exposed to the shock and zero else. The predicted wage effects of these shocks are expressed in percent of the initial wage shock in order to make them independent of the magnitude of the shock. A value of, for example, $\widehat{u}_r = 102$ for Fulton county, GA, means that the wage rate in Fulton is predicted to increase by the shock itself and an additional 2% of the magnitude of the shock. And the value of $\widehat{u}_r = 2.5$ for Cobb county, GA, a neighbor to Fulton, means that the wage rate in Cobb is predicted to increase by 2.5% of the magnitude of the shock in Fulton. NYC serves as an example of a large metropolitan center in a density populated region (New England), Atlanta (Fulton county), GA, as one of a metropolitan center in a less densely populated region, and Douglas county, SD, as one of a small county with a population of 3,000 (7 per square mile) in a rural region.

Figure 1. Wage effects of wage shocks in New York city, Atlanta, GA, and Douglas, SD, predicted by model 0



Notes: New York city comprises 5 counties, Bronx, Kings, Manhattan, Queens and Richmond; Atlanta one county, Fulton, GA.

Model 0 accounts for 58% of the variations in wage shocks, according to the regression fit statistic, R^2. This value is lower than that of the theoryless model 4, which accounts for 59%.[20] Model 0 thus fits the data worse than a theoryless model. In addition to this, the R^2 of model 0 decreases continuously as the sluggishness parameter ϕ_0 increases towards its threshold of 0.065. That is, the sluggishness parameter that maximizes the fit of model 0 is actually $\phi_0 = 0$. Model 0 is identical to model 3 in this case, for which we obtain a higher R^2 of 0.588.[21] This implies that, even though we account for significant sluggishness of the adjustments of prices and migration to a new equilibrium after a shock, and even though we obtain plausible parameter estimates as well as plausible predictions of responses of workers and firms to shocks, we do not find the NEG model as a whole to explain the regional distribution of economic activity and wages in the U.S. well.

An inspection of the regression results for the restricted models 1 and 2 help in exploring the reasons why the NEG model as a whole fits the data poorly. Model 1 differs from the model 0 only in that it features fixed rather than flexible prices, and model 2 differs from model 0 only in that it features immobile rather than mobile labor. The regression results for model 1 are very similar to those for model 0. It just fits the data even slightly worse than model 0, according to its R^2 of 0.578. This suggests that it is not the price adjustment mechanisms hypothesized by the NEG model that make it fit the data poorly. The regression results for model 2 are—for a maximal sluggishness parameter of $\phi_2 = 0.58$[22] that supports a fixed point for this model—also fairly similar to those for model 0, even though the substitution elasticity (3.75) is estimated to be somewhat higher and the partial adjustment parameter (0.714) somewhat lower. Still, model 2 fits the data considerably better than model 0. The R^2 for model 2 is 0.61, which is by about 3 percentage points higher than that for model 0, and it is also higher than that for the theoryless model 4. In addition to this, the R^2 of model 2 increases continuously with increasing sluggishness parameter, ϕ_2. This suggests that it is the migration adjustment mechanisms hypothesized by the NEG model that make model 0 fit the data rather poorly.

Model 3, which features fixed prices and immobile labor, fits, like models 0 and 1, the data rather poorly. The R^2 for this model is 0.588, which is also lower than that for the theoryless model. The fact that model 3 differs

[20] The R^2s of the five models generally do not differ too much from each other. They vary by less than three percentage points. This is possibly due to the fact that the spatially lagged dependent variable contributes only to a limited extent to explaining variations in regional wages.

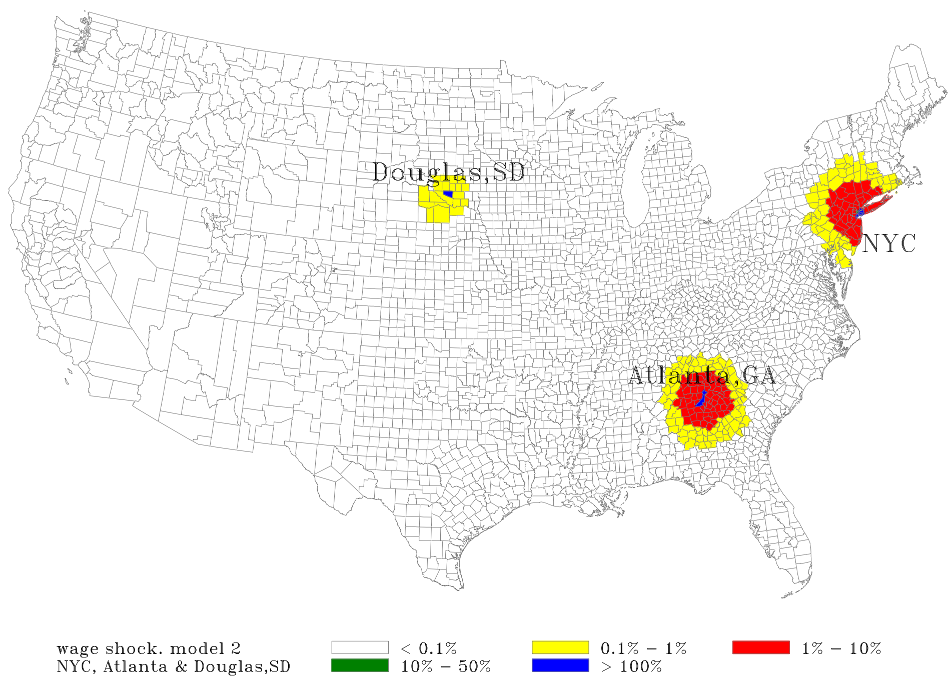
[21] This result is not due to the fact that ϕ_0 discounts both sluggishness of price adjustments and of migration simultaneously. If the sluggishness parameters for price adjustments and migration are allowed to differ from each other, we obtain the highest R^2 for a migration-sluggishness parameter of 0 and a price-sluggishness parameter of 0.58. Model 0 is identical to model 2 in this case, which features immobuile labor but flexible prices.

[22] This value is not too implausible either in light of the fact that some prices are fixed by longer-term contracts, or are too costly to be adjusted frequently.

from model 2, which fits the data best, only in that it features fixed rather than flexible prices suggests that the price adjustment mechanisms hypothesized by the NEG model receive support from the data. And the fact that model 3 differs from model 1, which fits the data worst, only insofar as migration adjustments are switched off corroborates our conclusion that the migration adjustment mechanisms hypothesized by the NEG model do not receive support from the data.

Even though model 2 fits the data only slightly better than model 0, according to the R^2, it fits the data in a different way. The bilateral regional wage elasticities ($\frac{\partial \ln w_r}{\partial \ln w_x}$, see Table 3), which arepositive or negative in model 0, are strictly non-negative and, on average, higher in model 2. In model 0, migration tends to moderate the magnitudes of the changes in prices and wages needed to restore equilibrium. In model 2, however, firms whose competitiveness deteriorates after a positive wage shock, and workers whose purchasing power deteriorates after such a shock, are not allowed to move to neighboring regions. All the adjustment pressure is bourne by prices and wages. The simulations of a wage shock in NYC, Atlanta and Douglas, SD, consequently show that model 2 predicts the wage effects of these shocks to be stronger and to attenuate slower with increasing distance than model 0 (Figure 2). It predicts the wage rates in, for example, the five counties of NYC to increase by 110% to 112% of the initial shock (model 0: 100.4%–101.6%), and the wage rates in counties neighboring NYC, such as Monmouth, NJ, or Hudson, NJ, by up to 11% of the shock (model 0: 2%).

Figure 2. Wage effects of wage shocks in New York city, Atlanta, GA, and Douglas, SD, predicted by model 2



Notes: New York city comprises 5 counties, Bronx, Kings, Manhattan, Queens and Richmond; Atlanta one county, Fulton, GA.

Sensitivity tests, presented in more detail in Appendix 2, indicate that the main results reported in this section are robust to the choice of the predetermined transport cost parameter, τ. We set this parameter to 0.02 in the baseline models because this value is close to the distance decay parameter of 0.0199 that maximizes the R^2 of our regression for the theoryless model 4 (see Table 2, last column). If we set it to a significantly lower value of 0.005, or to a significantly higher value of 0.035, the main results remain the same: The models that feature immobile labor fit the data better than those that feature immobile labor, the models that feature flexible prices fit the data better than those that feature fixed prices, and the model that features immobile labor and flexible prices jointly fits the data best. The parameter values differ across the models for different transport cost parameters, though. The substitution elasticity, σ, tends to decrease, and the sluggishness parameters, ϕ, to increase with increasing transport costs. The sensitivity tests also indicate that our main results are not entirely driven by variations over time of the human-capital intensities of the regional workforces. We show that the main results hold if we use, instead of the observed wage rates, hypothetical wage rates that are net of region- and time-specific skill premia.

In summary, using a new strategy to test a Krugman-type NEG model, we find that the NEG model as a whole does not receive support from U.S. data. Regional wages in the U.S. do not respond to local wage shocks in the way hypothesized by the NEG model. The main reason for this is that, even though workers are comparatively mobile in the U.S., the wages do not reflect the migration adjustment mechanisms hypothesized by the NEG model. Either the model does not predict the directions and relative magnitudes of migration between regions correctly, or it does not predict the repercussions of this migration on regional wages correctly. By contrast, regional wages in the U.S. do respond to shock-induced changes in consumer prices in the way hypothesized by the NEG model, according to our empirical results.

Our result that the hypotheses of the NEG model with respect to migration adjustments are not supported by the data stands in contrast to the results reported by several other studies, most of which focus on Europe. Redding and Sturm (2008), for example, find that an NEG model very similar to the one used in our study correctly predicts migration away from the inner-German border after the division of Germany in the 1940s. And several other studies, including Crozet (2004), Ottaviano and Pinelli (2006), Pons et al. (2007), and Paluzie et al. (2009), report evidence on a positive relationship between migration and market potentials for several European countries. One possible explanation for this contrast may be that we subject NEG to a more rigorous test than virtually all other studies that test NEG models. We use all equilibrium conditions of the NEG model and force the equilibrium values of several observable endogenous variables to coincide with the data. Another possible explanation is that the time period of one year we use to identify the responses to shocks is too short for workers to respond to wage shocks by migration. This possible explanation may be explored in more detail by future work that employs the strategy proposed in this paper to analyze longer-term responses to wage shocks. A third possible explanation is that more migrants in the U.S. than in Europe prefer moving to nice weather over moving to the best-paying places in terms of real wages. Empirical studies like Shapiro (2008), Glaeser and Tobio (2007), or Rappaport (2007, 2008) suggest that migration in the U.S. has increasingly been shaped by regional differences in consumption amenities like favorable climatic conditions. To explore this explanation, future work may use the strategy proposed in this paper to test NEG models for European data on the one hand, and NEG models that take amenities into account and model migration choices more explicitly, such as that in Tabuchi and Thisse (2002), for U.S. data, on the other.

6 Conclusion

We propose a new strategy that facilitates testing nonlinear NEG models more rigorously than the strategies employed before. This strategy allows us to take into account both data on several observable endogenous variables of the model, and the whole NEG model, that is, all equilibrium conditions that determine these endogenous variables. The strategies employed before facilitate either using extensively data on observable endogenous variables at the expense of not taking into account those equilibrium conditions of the model that determine these variables, or taking into account all equilibrium conditions of the model at the expense of not being able to use extensively data on observable endogenous variables. Our strategy moreover facilitates assessing selected elements of the NEG model separately, such as the effects of labor mobility or of changes of consumer price indices.

We employ this strategy to test a standard multiregion nonlinear Krugman-type NEG model taken right out of the textbook by Fujita et al. (1999) for a panel of U.S. counties. Our results suggest that the model explains the regional distributions of economic activity and wages in the U.S. rather poorly because the data do not support the predictions of the NEG model with respect to either the causes or the consequences of interregional migration. The data do, by contrast, support the predictions of the NEG model with respect to the interdependencies between regional wages and the prices of traded goods.

There are several potentially fruitful avenues for future research on refining the strategy we propose in this paper. One avenue is exploring ways of evaluating the longer-term effects of wage shocks. To simplify the estimations, we approximate the equilibrium values of endogenous variables of the NEG model by their observed long-run averages, and focus on evaluating short-term responses to disequilibriating wage shocks. This focus on short-term responses may lead to an underestimation of those responses that are, like migration, subject to significant costs. A second avenue for future research is broadening the scope of the shocks used to evaluate NEG model. In addition to wage shocks, employment shocks may be taken into account by mapping the NEG model into a system of two estimable interdependent equations, one wage equation and one employment equation, rather than into a single wage equation. This expansion of the empirical model will also facilitate evaluating in more detail whether the data do not support the hypotheses of the NEG model about the causes or the consequences of interregional migration. Finally, a third avenue is developing powerful statistical tests that help discriminate between spatial autoregressive models with different spatial weights matrices.

7 Appendices

Appendix 1: Derivation of the empirical model

This appendix derives the spatial weights matrix $\mathbf{J}^w = (\frac{\partial \ln w_r}{\partial \ln w_x})_{(R\times R)}$ in equation (13) in Section 3.1 from the equilibrium conditions (1)-(4) of the multiregion Krugman-type NEG model discussed in Section 2. After taking natural logarithms of (1)-(3) and factoring out the constant terms C_1 and C_2 in (1) and (2), this system of $3R$ equations reads:

$$\ln w_r = \frac{1}{\sigma}\ln\mu + \frac{1}{\sigma}\ln\left[\sum_{s=1}^{R} T_{sr}^{1-\sigma} g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)\right], \quad (29)$$

$$\ln g_r = \ln\left(G_r/C_2\right) = \frac{1}{1-\sigma}\ln\left[\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M\right], \quad (30)$$

$$\ln w_r = \ln w_i + \mu\left(\ln g_r - \ln g_i\right), \qquad i \neq r, \quad (31)$$

$$\ln L^M = \ln\left(\sum_{s=1}^{R} L_s^M\right), \qquad r = 1,...,R. \quad (32)$$

The R^2 bilateral spatial weights $\frac{\partial \ln w_r}{\partial \ln w_x}$ are obtained by totally differentiating the wage equation (30) separately for each pair of regions r and x. This yields

$$\begin{aligned}\frac{\partial \ln w_r}{\partial \ln w_x} = & \frac{1}{\sigma}\frac{T_{xr}^{1-\sigma} g_x^{\sigma-1} w_x L_x^M}{\sum_{s=1}^{R} T_{sr}^{1-\sigma} g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)} \\ & + \frac{1}{\sigma}\sum_{s=1}^{R}\frac{T_{sr}^{1-\sigma} g_s^{\sigma-1} w_s L_s^M}{\sum_{s=1}^{R} T_{sr}^{1-\sigma} g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)}\frac{\partial \ln L_s^M}{\partial \ln w_x} \\ & + \frac{(\sigma-1)}{\sigma}\sum_{s=1}^{R}\frac{T_{sr}^{1-\sigma} g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)}{\sum_{s=1}^{R} T_{sr}^{1-\sigma} g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)}\frac{\partial \ln g_s}{\partial \ln w_x}, \quad (33)\end{aligned}$$

$r, x = 1, ..., R$. After defining

$$f_{rs}^{y} \quad : \quad = \frac{T_{sr}^{1-\sigma} g_s^{\sigma-1} w_s L_s^M}{\sum_{s=1}^{R} T_{sr}^{1-\sigma} g_s^{\sigma-1} \left(w_s L_s^M + L_s^A\right)} \geq 0,$$
$$f_{rs}^{g} \quad : \quad = (\sigma - 1) \frac{T_{sr}^{1-\sigma} g_s^{\sigma-1} \left(w_s L_s^M + L_s^A\right)}{\sum_{s=1}^{R} T_{sr}^{1-\sigma} g_s^{\sigma-1} \left(w_s L_s^M + L_s^A\right)} > 0,$$

(33) can be expressed in a more compact form as

$$\frac{\partial \ln w_r}{\partial \ln w_x} = \frac{1}{\sigma} \left[f_{rx}^{y} + \sum_{s=1}^{R} f_{rs}^{y} \frac{\partial \ln L_s^M}{\partial \ln w_x} + \sum_{s=1}^{R} f_{rs}^{g} \frac{\partial \ln g_s}{\partial \ln w_x} \right]. \tag{34}$$

Since the elasticities f_{rs}^{y} and f_{rs}^{g} are independent of values from region x, we can straightforwardly collect the interdependencies in wage rates between all pairs of regions in a single spatial weights matrix $\mathbf{J}^w$, which is given by

$$\mathbf{J}^w = \left(\frac{\partial \ln w_r}{\partial \ln w_x} \right)_{(R \times R)} = \frac{1}{\sigma} \left(\mathbf{f}^y + \mathbf{f}^y \mathbf{J}^L + \mathbf{f}^g \mathbf{J}^g \right), \tag{35}$$

where $\mathbf{f}^y = (f_{rs}^y)_{(R\times R)}$, $\mathbf{f}^g = (f_{rs}^g)_{(R\times R)}$,$\mathbf{J}^g = \left(\frac{\partial \ln g_s}{\partial \ln w_x}\right)_{(R\times R)}$, and $\mathbf{J}^L = \left(\frac{\partial \ln L_s^M}{\partial \ln w_x}\right)_{(R\times R)}$. The matrices $\mathbf{f}^y$, and $\mathbf{f}^g$ are assumed to be exogenous in the empirical investigation. In addition to the structural parameters and exogenous variables of the NEG model, they depend on the equilibrium wages and manufacturing employment quantities. The matrices $\mathbf{J}^L$ and $\mathbf{J}^g$ are endogenous, however, and will be eliminated from (35) in the remaining two steps.

To eliminate $\mathbf{J}^g$, we totally differentiate the CPI (30) separately for each pair of regions r and x, which yields

$$\frac{\partial \ln g_r}{\partial \ln w_x} = \frac{T_{rx}^{1-\sigma} w_x^{1-\sigma} L_x^M}{\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M} + \frac{1}{1-\sigma} \sum_{s=1}^{R} \frac{T_{rs}^{1-\sigma} w_s^{1-\sigma} L_x^M}{\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M} \frac{\partial \ln L_s^M}{\partial \ln w_x}, \tag{36}$$

$r, x = 1, ..., R$. After defining

$$c_{rs} := \frac{T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M}{\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M} \geq 0, \tag{37}$$

(36) can be expressed in a more compact form as

$$\frac{\partial \ln g_r}{\partial \ln w_x} = c_{rx} + \frac{1}{1-\sigma} \sum_{s=1}^{R} c_{rs} \frac{\partial \ln L_s^M}{\partial \ln w_x},$$

or as

$$\mathbf{J}^g = \mathbf{c}^g + \frac{1}{1-\sigma}\mathbf{c}^g\mathbf{J}^L, \tag{38}$$

in matrix notation, where $\mathbf{c}^g = (c_{rx})_{(R\times R)}$. $\mathbf{c}^g$ is assumed to be exogenous in the empirical investigation.

Finally, to eliminate $\mathbf{J}^L$, we interpret the $(R-1)$ independent equations (31) together with (32) as a system of R equations that determine the labor market equilibrium. Choosing, without loss of generality, the ith region as a reference region, and substituting the definition of the regional price indices, g_s from (30) into equation (31), this system of equation is given by

$$\begin{aligned} 0 &= -\ln w_r + \ln w_i \\ &\quad +\frac{\mu}{1-\sigma}\left(\ln\left[\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M\right] - \ln\left[\sum_{s=1}^{R} T_{is}^{1-\sigma} w_s^{1-\sigma} L_s^M\right]\right), \quad (39) \\ 0 &= -\ln L^M + \ln\left(\sum_{s=1}^{R} L_s^M\right), \quad (40) \end{aligned}$$

where $r = 1, ..., i-1, i+1, ..., R$. This system of R equations determines implicitly $L_1^M, .., L_R^M$ as a function of $\ln w_1, ..., \ln w_R$. We can thus totally differentiate (39) and (40) separately for each pair of regions r and x and solve for $\mathbf{J}^L$. The derivatives of (39) are

$$\begin{aligned} 0 &= -\psi_r + \psi_i \\ &\quad +\mu\left[\frac{T_{rx}^{1-\sigma} w_x^{1-\sigma} L_x^M}{\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M} + \frac{1}{1-\sigma}\sum_{s=1}^{R}\frac{T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M}{\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M}\frac{\partial \ln L_s^M}{\partial \ln w_x}\right] \\ &\quad -\mu\left[\frac{T_{ix}^{1-\sigma} w_x^{1-\sigma} L_x^M}{\sum_{s=1}^{R} T_{is}^{1-\sigma} w_s^{1-\sigma} L_s^M} + \frac{1}{1-\sigma}\sum_{s=1}^{R}\frac{T_{is}^{1-\sigma} w_s^{1-\sigma} L_s^M}{\sum_{s=1}^{R} T_{is}^{1-\sigma} w_s^{1-\sigma} L_s^M}\frac{\partial \ln L_s^M}{\partial \ln w_x}\right], \end{aligned}$$

where $r \neq i$, $\psi_r = \begin{cases} 1 \text{ for } r = x \\ 0 \text{ for } r \neq x \end{cases}$, and $\psi_i = \begin{cases} 1 \text{ for } i = x \\ 0 \text{ for } i \neq x \end{cases}$. The derivative of (40) is $0 = \frac{1}{L}\sum_{s=1}^{R}\frac{\partial \ln L_s^M}{\partial \ln w_x}$. Using the notation in (**??**) and (37), this system of R^2 equations can be expressed in a more compact form as

$$\begin{aligned} 0 &= -\psi_r + \psi_i + \mu\left(c_{rx} - c_{ix}\right) + \frac{\mu}{1-\sigma}\sum_{s=1}^{R}\left(c_{rx} - c_{ix}\right)\frac{\partial \ln L_s^M}{\partial \ln w_x}, \\ 0 &= \frac{1}{L}\sum_{s=1}^{R}\frac{\partial \ln L_s^M}{\partial \ln w_x}, \end{aligned}$$

or as

$$\mathbf{0}_{R\times R} = \mu\mathbf{c}^L + \frac{\mu}{1-\sigma}\mathbf{B}^L\mathbf{J}^L. \tag{41}$$

in matrix notation. If region 1 is chosen as the reference region ($i = 1$), the $(R \times R)$ matrix $\mathbf{c}^L$ reads

$$\mathbf{c}^L = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ c_{21} - c_{11} + 1/\mu & c_{22} - c_{12} - 1/\mu & \cdots & c_{2R} - c_{1R} \\ c_{31} - c_{11} + 1/\mu & c_{32} - c_{12} & \cdots & c_{3R} - c_{1R} \\ \vdots & \vdots & \ddots & \vdots \\ c_{R1} - c_{11} + 1/\mu & c_{R2} - c_{12} & \cdots & c_{RR} - c_{1R} - 1/\mu \end{bmatrix},$$

and the $(R \times R)$ matrix $\mathbf{B}^L$,

$$\mathbf{B}^L = \begin{bmatrix} \frac{1-\sigma}{\mu L} & \frac{1-\sigma}{\mu L} & \cdots & \frac{1-\sigma}{\mu L} \\ c_{21} - c_{11} & c_{22} - c_{12} & \cdots & c_{2R} - c_{1R} \\ c_{31} - c_{11} & c_{32} - c_{12} & \cdots & c_{3R} - c_{1R} \\ \vdots & \vdots & \ddots & \vdots \\ c_{R1} - c_{11} & c_{R2} - c_{12} & \cdots & c_{RR} - c_{1R} \end{bmatrix}.$$

We obtain the explicit solution for $\mathbf{J}^L$ by solving (41) for $\mathbf{J}^L$, which yields

$$\mathbf{J}^L = (\sigma - 1) \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L. \tag{42}$$

$\mathbf{c}^L$ and $\mathbf{B}^L$ are assumed to be exogenous in the empirical investigation. By substituting (38) and (42) into (35), we obtain equation (13) in Section 3.1,

$$\mathbf{J}^w = \frac{1}{\sigma} \left[\mathbf{f}^y + (\sigma - 1) \mathbf{f}^y \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L + \mathbf{f}^g \left(\mathbf{c}^g + \mathbf{c}^g \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L\right)\right].$$

Appendix 2: Sensitivity analysis

Choice of the transport cost parameter

To check to what extent the results presented in Section 5 depend on the choice of the transport cost parameter, $\tau = 0.02$, we reestimate models 0–3 for $\tau = 0.005$ and $\tau = 0.035$. A transport cost parameter of $\tau = 0.005$ (0.035) implies that 50% of the iceberg is gone after 139 miles (20 miles), and 90% after 460 miles (132 miles). From Table A1, which reports the results of these sensitivity tests, we observe that the main inferences drawn from our baseline specification do not depend on the choice of the transport cost parameter. Irrespective of the value of the transport cost parameter, the model that features flexible prices and immobile labor, model 2, fits the data better than all other models, according to the R^2s, while the two models that feature mobile labor fit the data worse than those that feature immobile labor. The estimated substitution elasticities, σ, and the maximal sluggishness parameters for prices and migration for which fixed points for σ exist in models 0–2, differ from those in the baseline specification, though. σ tends to decrease, and ϕ_j to increase with increasing transport cost parameter.

Table A1. Sensitivity tests: Different transport cost parameters

model	0		1		2		3	
	Predetermined parameters in spatial weights							
τ	0.005	0.035	0.005	0.035	0.005	0.035	0.005	0.035
σ	5.67	2.7	5.8	2.8	8.0	4.75	2.974	1.507
μ	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
ϕ	0.003	0.115	0.003	0.116	0.62	0.741	1	1
	Estimated parameters							
σ	5.671	2.700	5.800	2.799	8.000	4.750	2.974	1.507
Std.dev.	(0.91)	(0.19)	(1.01)	(0.27)	(0.49)	(1.62)	(0.38)	(0.10)
θ	0.749	0.744	0.749	0.756	0.731	0.608	0.748	0.738
Std.dev.	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.08)	(0.003)	(0.003)
R^2	0.583	0.581	0.583	0.570	0.595	0.714	0.584	0.590
1^{st}st.R^2	0.800	0.644	0.711	0.590	0.777	0.628	0.836	0.808

Notes: Nonlinear 2SLS regressions of SAR(1) model (27) with spatial weights $\mathbf{W}_{0,\phi_0}$ (equation 23), $\mathbf{W}_{1,\phi_1}$ (22), $\mathbf{W}_{2,\phi_2}$ (21), or $\mathbf{W}_3$ (19) for 3076 U.S. counties 1990–2005 (46,140 observations).

Control for human-capital intensities

Do the main results of this paper still hold after regional differences in human-capital intensities are controlled for? To answer this question, we reestimate models 0–3 using filtered regional wage rates that are net of skill premia, henceforth denoted by $\widehat{w}_{rt}$, instead of the observed regional wage rates, w_{rt}.

We filter the wage rates by using a simple panel OLS regression. We regress the observed wage rates on the (estimated)[23] contemporary shares of persons with a bachelor degree and a high school diploma in the total population aged 25 or more as well as on a set of time dummies,

$$w_{rt} = \alpha_1 h_{rt}^{bach} + \alpha_2 h_{rt}^{high} + \iota_t + \xi_{rt}, \tag{43}$$

and then calculate the filtered wage rates, which we hypothesize to be net of skill premia, as

$$\widehat{w}_{rt} = \iota_t + \xi_{rt}. \tag{44}$$

The time dummies in (43) account for inflationary increases of wages over time. Notice that we assume the marginal skill premia (parameters α_1 and α_2) to be the same in all counties and all years for simplicity.

Table A2 reports the regression results for models 0–3 with filtered wages $\widehat{w}_{rt}$ (44) instead of the observed wages w_{rt}. It shows that our main results, presented in Table 2, are not solely driven by regional differences in human-capital intensities: The NEG model still contributes significantly to explaining regional wages, and model 2, which represents the general equilibrium NEG model with immobile labor, still fits the data better than all other models, including those with mobile labor (models 0 and 1). In line with Head and Mayer (2006), we find that human capital accounts for a fraction but not all of the spatial autocorrelation in regional wages. The point estimates for the substitution elasticity, σ, are generally higher for the filtered than the observed wages, which implies that the spatial lag parameter $\rho = 1/\sigma$ is lower. The sluggishness parameter ϕ is estimated to be generally lower for the filtered than for the original wages. It is, however, still higher for our preferred model 2 than for the models with mobile labor (models 0 and 1).

Table A2. Sensitivity tests: Human-capital adjusted wages

model	0	1	2	3
Predetermined parameters in spatial weights				
σ	5.9	5.81	9.761	4.672
τ	0.02	0.02	0.02	0.02
μ	0.5	0.5	0.5	0.5
ϕ	0.019	0.013	0.15	1
Estimated parameters				
σ	5.900	5.809	9.761	4.672
(std.dev.)	(1.41)	(1.44)	(2.82)	(0.95)
θ	0.705	0.708	0.683	0.704
(std.dev.)	(0.006)	(0.005)	(0.01)	(0.005)
R^2	0.562	0.558	0.589	0.564
1^{st}st.R^2	0.539	0.542	0.544	0.571

[23] The method for estimating the shares of persons with a bachelor and a high-school degree in each county and year, h_{rt}^{bach} and h_{rt}^{high}, is described in more detail below.

Notes: Nonlinear 2SLS regressions of SAR(1) model (27) with spatial weights $\mathbf{W}_{0,\phi_0}$ (equation 23), $\mathbf{W}_{1,\phi_1}$ (22), $\mathbf{W}_{2,\phi_2}$ (21), or $\mathbf{W}_3$ (19) for 3076 U.S. counties 1990–2005 (46,140 observations). See the text for a description of the method use to estimate the human-capital adjusted wages.

We estimate the annual data on educational attainment of residents at the county level, h_{rt}^{bach} and h_{rt}^{high}, from two data sources: data on the educational attainment of residents at the county level in the census years, 1990 and 2000, published by the U.S. census bureau (USCB), and data on the educational attainment of residents at the state level in all years, 1990–2005, also published by the USCB. To estimate data on the educational attainment of residents at the county level for each intercensal year, 1991–1999 and 2001–2005, we proceed in two steps: The first step yields preliminary estimates of the number of persons in three exhaustive and mutually exclusive educational attainment groups in each county and intercensal year from a linear interpolation of the census data. The second step yields final estimates that match total county populations and state-level shares of skills groups in total populations. The three educational attainment (skill) groups are (i) persons without a high school diploma, (ii) persons with high school diploma but no bachelor degree, and (iii) persons with a bachelor degree or higher.

In the first step, we estimate the preliminary number of persons by skill group and county in the intercensal years by using the shares of each county-skill group in total state population (aged 25 or more) in the two census years, 1990 and 2000, as an input. Letting M_{rsjt} denote the observed number of persons in skill group j ($j = bach, high, others$) in county r in state s ($r = 1, ..., N_s$, $s = 1, ..., 49$, N_s: no of counties in state s) at time t, we define the share of a county-skill group in total state population as $\eta_{rsjt} := M_{rsjt}/M_{st}$, where $M_{st} = \Sigma_{r=1}^{N_s} \Sigma_j M_{rsjt}$. Given $\eta_{jrs1990}$ and $\eta_{rsj2000}$ from the censuses, we set the preliminary shares of county-skill groups in total state population to

$$\eta_{rsjt}^0 = \begin{cases} \eta_{rsj1990} + \left(\eta_{rsj2000} - \eta_{rsj1990}\right) \cdot \frac{(t-1990)}{10} & \text{for } t = 1991, ..., 1999 \\ \eta_{rsj2000} & \text{for } t = 2001, ..., 2005. \end{cases}$$

These shares are then transformed back into absolute population numbers, M_{rsjt}^0, by multiplying them by M_{st},the total state populations aged 25 or more in the respective year. The resulting absolute population numbers M_{rsjt}^0 sum up across all skill groups and counties to total state population in each year by definition. They do, however, not necessarily sum up across counties to the state-level population numbers by skill group, or across skill groups to total county populations.

To ensure that the M_{rsjt}^0 sum up to the state-level population numbers by skill group, M_{sjt}, and the total county populations in each year, M_{rst}, we employ a simple nonlinear program for each state and intercensal year, which can be characterized by

$$min\ F = \sum_{r=1}^{N_s} \sum_{j} M^0_{rsjt}(X_{rsjt} - 1)^2$$

$$\begin{aligned} s.t.\ \sum_{r=2}^{N_s} M^0_{rsjt} X_{rsjt} &= M_{jst} \\ \sum_{j} M^0_{rsjt} X_{rsjt} &= M_{rst} \\ X_{rsjt} &\geq 0 \end{aligned}$$

$s = 1, ..., 49$; $t = 1991 - 1999,\ 2001 - 2005$.[24] This program yields, for each state and year, an $(N_s \times 3)$ matrix of adjustment parameters $\widehat{X}_{rsjt}$ from which we calculate our final estimates of county-skill group population numbers as $\widehat{M}_{rsjt} = M^0_{rsjt}\widehat{X}_{rsjt}$. The distribution of the $\widehat{M}_{rsjt}$ matches the observed state-level skill group and region totals while differing as little as possible from the distribution of the M^0_{rsjt}. The estimated shares of persons with a bachelor degree or high school diploma in the total population aged 25 or more in county r, are then given by $h^{bach}_{rt} = \widehat{M}_{rs,bach,t}/M_{rst}$ and $h^{high}_{rt} = \widehat{M}_{rs,high,t}/M_{rst}$.

[24] The USCB total state population numbers differ slightly between the two statistics of state-level skill group and county population estimates. We assume that the state-level population estimates are more accurate than the county-level estaimates. The total county populations are therefore determined by multiplying the share of each county in total state population, calculated from the USCB county-level estimates, by total state population, as given by the state-level estimates. State-level educational attainment data for the three skill groups used here is not available for the years 1991 and 1992. They are estimated by linear interpolation from the corresponding data for the years 1990 and 1993.

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