Testing Nonlinear New Economic Geography Models

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Abstract

This paper proposes a new approach for testing nonlinear New Economic Geography (NEG) models. The approach maps all equilibrium conditions of an NEG model into an estimable spatial autoregressive model of order one—SAR(1) model—in regional wages, which reflects the sensitivity, predicted by the NEG model, of each region's wage rate to a wage shock elsewhere. The approach also facilitates testing selected features of the NEG model separately. An illustration shows that the Krugman model does not fit the data for US counties 1990–2005 because it does not predict the migration patterns triggered by wage shocks correctly.

JEL classification: C23, C52, R12

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1 Introduction

In New Economic Geography (NEG), empirics is lagging behind theory. Following Krugman (1991), a vibrant theoretical literature has developed a rich variety of general equilibrium NEG models that explain the spatial distribution of economic activity as resulting from the trade-off between microeconomically well-founded agglomeration and dispersion forces.[1] These models, and especially the non-linear models among them, are not easily brought to the data because they give rise to complex systems of interdependent nonlinear equilibrium conditions.[2] Most of the empirical NEG literature focuses on testing only selected

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[1] NEG textbooks include Fujita et al. (1999), Baldwin et al. (2003), Combes et al. (2008), and Brakman et al. (2009). Surveys of the empirical literatureee include Head and Mayer (2004), Combes et al. (2009), Brakman et al. (2009), Redding (2010) and Brülhart (2011).

[2] Analytically solvable, "linear" NEG models (Ottaviano et al. 2002) reduce this complexity but miss some of the feedbacks present in nonlinear models.

equilibrium conditions or propositions of NEG models, which implies ignoring potentially important features of the theory.[3] A few studies, notably Behrens et al. (2009b) and Combes and Lafourcade (2011), have recently proposed ways of bringing NEG models as a whole to the data, though. These studies have, however, focused on NEG models that assume regions to interact only through trade but not through migration of workers. It is essentially this spatial mobility of workers—or, more precisely, of purchasing power—that distinguishes NEG from (international) trade theory in our view (Bickenbach and Bode forthcoming). Behrens et al. (2009b) combine estimation and simulation techniques to fit the general equilibrium of their model iteratively to the data. They repeatedly estimate one equilibrium condition, the trade equation, to obtain a value of the trade cost parameter, and simulate the other equilibrium conditions to obtain values of selected other structural parameters. While constraining the other equilibrium conditions are by the estimated trade cost parameter, and the trade equation by the simulated structural parameters, their iterative procedure eventually converges to a stable set of structural parameters. Combes and Lafourcade (2011) linearize all equilibrium conditions of their multi-region and multi-industry NEG model by Taylor expansion at the perfect-integration equilibrium with zero all transport costs. This approximation allows them to reduce all equilibrium conditions to a single linear regression model that can be estimated with standard econometric techniques.

In the approach proposed in the present paper, we linearize the wage equation, one of the equilibrium conditions of the underlying NEG model, to obtain a spatial autoregressive model of order one—SAR(1) model—in regional wages, and then use the remaining equilibrium conditions to eliminate all endogenous variables except the regional wages from the empirical model. Unlike Combes and Lafourcade (2011), we expand the wage equation at the general equilibrium under positive rather than zero transport costs. This keeps approximation errors as small as possible. The resulting empirical SAR(1) model explains the deviation of the wage rate in each region from its equilibrium value by the weighted sum of the deviations of the wage rates in all regions from their equilibrium values. The bilateral regional weights are the equilibrium elasticities of the wage rate in one region with respect to the wage rate in another region implied by the NEG model. These weights depend nonlinearly on all the parameters and equilibrium values of the endogenous variables of the NEG model and reflect all the direct (bilateral) and indirect (through third regions) channels through

[3] On the one hand, studies like Hanson (2005), Redding and Venables (2004) or Mion (2004) estimate an augmented wage equation, which takes only a subset of the equilibrium conditions of NEG models into account. This comes at the cost of ignoring, among others, the interdependence between production costs and sales prices for traded goods. It also creates serious endogeneity problems. On the other hand, studies like Davis and Weinstein (1999; 2002) or Bosker et al. (2007) test some general propositions of NEG like the home market effect or the existence of multiple equilibria. These tests cannot discriminate between NEG and other theories consistent with those propositions. Moreover, the propositions, which are usually derived from two-region models, may not carry over to multiregional settings (Behrens et al. 2009a).

which regions interact in the NEG model. In addition to interregional trade, these channels may also include interregional migration of workers or firms, depending on the underlying NEG model.

By mapping the NEG model into a SAR(1) model, the approach not only exploits the natural complementarity between NEG and spatial econometrics (Behrens and Thisse 2007). It also provides a consistent foundation of spatial weights in economic theory, the lack of which has recently put spatial econometrics under serious criticism (Corrado and Fingleton 2012, Gibbons and Overman 2012).

The empirical SAR(1) model can be estimated by employing standard spatial econometric techniques for cross-section or panel data.[4] The estimation is, however, complicated by the fact that the spatial weights, and thus the (unknown) general equilibrium of the NEG model, must be quantified prior to the estimation. The estimation is thus subject to the correct quantification of all parameters and all endogenous variables of the NEG model. In addition to this, only one structural parameter of the NEG model, the substitution elasticity, can be estimated while the other parameters must be fixed a priori. The substitution elasticity enters not only the spatial weights but also the estimated parameter of the spatial lag, however. The SAR(1) model must therefore be estimated iteratively in order to search a fixpoint for the substitution elasticity. The estimated value of the substitution elasticity in the parameter of the spatial lag must be equal to its predetermined value in the spatial weights. This fixpoint closes the linearized NEG model. If no such fixpoint exists, the NEG model obviously doesn't fit the data. If a fixpoint exists, and if the estimate of the substitution elasticity is significant, one may generally conclude that the NEG model fits the data.[5] One may, however, want to test additionally if the NEG-based model fits the data better than some theoryless benchmark model.

In addition to testing the full NEG model, the approach proposed here also allows testing selected features of this model separately. These tests, which are, to our knowledge, novel in the empirical NEG literature, are done by imposing appropriate restrictions on the NEG model, mapping this restricted model into another SAR(1) model and testing if the SAR(1) model representing the unrestricted NEG model fits the data better than that representing the restricted NEG model. Since the restrictions affect only the magnitudes of the spatial weights, these tests amount to tests of spatial weights matrices against each other. The features that may be tested include the interdependencies between

[4] See LeSage and Pace (2009) or Anselin (2010) for recent surveys of the spatial econometric literature.

[5] Existence of several fixpoints of the substitution elasticity will point at multiple equilibria. Note that our definition of multiple equilibria differs from that in the theoretical literature. In the theoretical literature, multiple equilibria means that more than one equilibrium spatial distribution of economic activity exists for a single set of structural parameters (including the substitution elasticity). In our case multiple equilibria means that more than one set of structural parameters is consistent with a given spatial distribution of economic activity.

wages and the prices of the heterogeneous good and that between wages and migration.

We introduce the approach for the basic Krugman model, taken right out of the textbook by Fujita, Krugman and Venables (Fujita et al. 1999: Chapter 4). We choose this model because it focuses, on the one hand, on the core ingredients to NEG while allowing regions to interact through both trade and migration. Once the method for bringing the core model to the data has been established, it may be adopted straightforwardly to test various other NEG models that modify or complement this core model. On the other hand, we choose the Krugman model because it does not have a closed-form solution, which is one of the main obstacles to bringing NEG models to the data. By overcoming this obstacle, the approach paves the way for rigorous and discriminatory empirical testing of NEG models.

We illustrate the empirical implementation of the approach by testing the Krugman model for a panel of 3,076 mainland U.S. counties 1990–2005. The Krugman model can be expected to fit the data rather poorly because it predicts too much agglomeration. Dispersion forces are too weak relative to agglomertation forces in this model. This allows us to check if our approach does indeed reject the full model, and if restricted versions of this model, which exclude elements that respond particularly sensitively to the agglomeration forces, fit the data better. We find that the full Krugman model does indeed fit the data very poorly while a restricted model where labor is assumed to be regionally immobile fits the data better. Due to the lack of strong enough dispersion forces, the Krugman model most likely exaggerates the incentives for migration. Even the restricted Krugman model does not fit the data better than a theoryless model where spatial interactions depend on geography only, however. This suggests that the Krugman model adds little to explaining the contemporary spatial distribution of economic activity in the US. Future, similarly rigorous tests of other, more sophisticated NEG model will show if this pessimistic conclusion extends to NEG more generally.

The plan of this paper is as follows. Section 2 sketches the Krugman model. Section 3 introduces the conceptual approach of mapping this model into the SAR(1) model. Section 3.1 derives the spatial weights of the SAR(1) model from the full Krugman model while Section 3.2 derives corresponding spatial weights from restricted versions of the Krugman model. Section 4 illustrates the empirical implementation of the approach, proposes an estimation strategy, and presents the estimation results. Finally, Section 5 concludes.

2 Theoretical model

We introduce the conceptual approach of testing NEG models for the multiregion version of Krugman (1991). Since the model is discussed in length in

Chapter 4 of Fujita, Krugman and Venables (Fujita et al. 1999: 43–59), we focus on its equilibrium conditions here. The model describes an economy that comprises R regions, indexed by r ($r = 1, ..., R$), two sectors, agriculture and manufacturing (superscripts A and M), and two types of labor, agricultural and manufacturing labor (L^A, L^M). The agricultural sector produces a homogeneous agricultural good at constant returns to scale, using agricultural labor as the only input. It employs a fixed, positive number of L_r^A immobile workers per region, each of which produces one unit of output. The agricultural good, which is the numeraire, is traded freely across regions. Its price (= agricultural wage rate) is one in all regions. The monopolistically competitive manufacturing sector produces a horizontally differentiated 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 the varieties produced by other manufacturing 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. Market entry into the manufacturing sector is free. Consumers in all regions have identical Dixit-Stiglitz preferences, reflected by a nested Cobb-Douglas-CES utility function that features love of variety.

The long-term general equilibrium of this model is characterized by market clearing for all goods and factors, zero profits in manufacturing and equalization of real manufacturing wages across all regions. This equilibrium requires solving the following system of $3R$ equations that simultaneously determine nominal wage rates and employment in the manufacturing sector, w_r and L_r^M, in all R regions:[6]

$$w_r = C_1 \left[\sum_{s=1}^{R} T_{sr}^{1-\sigma} G_s^{\sigma-1} \left(w_s L_s^M + L_s^A \right) \right]^{\frac{1}{\sigma}}, \quad r = 1, ..., R \tag{1}$$

$$G_r = C_2 \left[\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M \right]^{\frac{1}{1-\sigma}}, \quad r = 1, ..., R \tag{2}$$

$$\frac{w_r}{G_r^{\mu}} = \frac{w_i}{G_i^{\mu}}, \qquad i \neq r, \tag{3}$$

$$\sum_{r=1}^{R} L_r^M = L^M, \tag{4}$$

where $C_1 = \mu^{\frac{1}{\sigma}} C_2^{\frac{1-\sigma}{\sigma}}$, and $C_2 = \frac{c}{\sigma-1} \left(\sigma^\sigma F \right)^{\frac{1}{\sigma-1}}$. $T_{rs} \left[= T \left(D_{rs}, \tau \right) > 1 \right]$ denotes the distance-related iceberg transport costs for shipping the manufacturing good

[6] Notice that equation (2) may be eliminated from this system of equations by supstituting it into (1) and (3). We keep it nonetheless because we will assess the interdependence between wages and price indices by restricting the consumer price index, G_r, to be exogenous and fixed below.

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 so-called wage equation. It determines the wage rate offered by a representative producer of the manufacturing good in each region for given income in all regions and given prices of all manufacturing varieties. We substitute the equilibrium condition that determines nominal income, $Y_s = w_s L_s^M + L_s^A$, into the wage equation for the sake of brevity. Equation (2) determines the local consumer price index (CPI) for the manufacturing good in each region for a given regional distribution of manufacturing employment and given regional wages. Equations (3) and (4) jointly determine the regional distribution of manufacturing workers. (3) is the no-migration condition, which requires real manufacturing wages to equate across all R regions, or, equivalently, real wages in all regions to be the same as those in a benchmark region i. Any inequality in real wages is assumed to trigger migration of manufacturing workers to those regions that offer higher real wages. Finally, (4) is the labor-market-clearing condition.

3 Conceptual approach

3.1 Full model

The approach we propose brings the whole Krugman model, characterized by equilibrium conditions (1)-(4), to the data. We essentially derive an estimable SAR(1) model in regional wages from the (logged) wage equation (1) by first-order Taylor approximation at the equilibrium of the NEG model, and parameterize the spatial weights of this SAR(1) model from all the (logged) equilibrium conditions of the Krugman model.

After taking natural logarithms of (1)-(4) and factoring out the constant terms C_1 and C_2 in (1) and (2), the system of $3R$ equilibrium conditions reads:

$$\ln w_r = \frac{1}{\sigma}\ln\mu + \frac{1}{\sigma}\ln\left[\sum_{s=1}^{R} T_{sr}^{1-\sigma} g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)\right], \quad (5)$$

$$\ln g_r = \ln\left(G_r/C_2\right) = \frac{1}{1-\sigma}\ln\left[\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M\right], \quad (6)$$

$$\ln w_r = \ln w_i + \mu\left(\ln g_r - \ln g_i\right), \qquad i \neq r, \quad (7)$$

$$\ln L^M = \ln\left(\sum_{r=1}^{R} L_r^M\right), \qquad r = 1, ..., R. \quad (8)$$

The Taylor approximation of the logged wage equation (5) at the general equilibrium of the NEG model yields a SAR model of order one in the deviations of the (logged) wage rates in all regions from their equilibrium values:

$$\ln w_r - \ln \widetilde{w}_r \approx \sum_{x=1}^{R} \frac{\partial \ln w_r}{\partial \ln w_x}\left(\sigma, \mu, \mathbf{T}, \mathbf{L}^A, \widetilde{\mathbf{w}}, \widetilde{\mathbf{L}^M}\right)\left(\ln w_x - \ln \widetilde{w}_x\right), \quad (9)$$

$r = 1, ..., R$, or, in matrix notation,

$$\ln \mathbf{w} - \ln \widetilde{\mathbf{w}} \approx \mathbf{J}^w \left(\ln \mathbf{w} - \ln \widetilde{\mathbf{w}}\right). \quad (10)$$

This SAR(1) model is the core of our regression model. $\mathbf{w}$ denotes the $(R \times 1)$ vector of regional wages (w_r), and a tilde characterizes equilibrium values. Equation (9) explains the deviation of the (logged) actual wage rate in any region r from its equilibrium value. $\ln w_r - \ln \widetilde{w}_r$, by the weighted sum of the deviations of the (logged) actual wage rates in all regions x, $x = 1, ..., R$, from their equilibrium values. The weights, $\partial \ln w_r / \partial \ln w_x$, are the equilibrium bilateral elasticities of the wage rate in a region r with respect to the wage rate in any region x. These R^2 bilateral weights, which are collected in the $(R \times R)$ spatial weights matrix $\mathbf{J}^w = (\partial \ln w_r / \partial \ln w_x)_{(R\times R)}$ in (10), depend on all the parameters and the equilibrium values of the endogenous variables of the NEG model. Each weight depends on (i) the structural parameters of the NEG model, which are the substitution elasticity σ, the income share spent on the manufacturing good, μ, and the full matrix of 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 equilibrium values of the manufacturing wage rate and manufacturing employment in all regions, $\widetilde{\mathbf{w}} = (\widetilde{w}_r)_{(R\times 1)}$ and $\widetilde{\mathbf{L}^M} = (\widetilde{L_r^M})_{(R\times 1)}$.

We parameterize each weight $\partial \ln w_r / \partial \ln w_x$ by partially differentiating (5) for region r by w_x:[7]

[7] We drop the tilde (˜) henceforth to simplify notation but note that all values of wages and manufacturing employment in (11) and the subsequent equations are equilibrium values.

$$
\begin{aligned}
\frac{\partial \ln w_r}{\partial \ln w_x} \quad = \quad & \frac{1}{\sigma}\frac{T_{xr}^{1-\sigma}g_x^{\sigma-1}w_x L_x^M}{\sum_{s=1}^{R}T_{sr}^{1-\sigma}g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)} \\
& +\frac{1}{\sigma}\sum_{s=1}^{R}\frac{T_{sr}^{1-\sigma}g_s^{\sigma-1}w_s L_s^M}{\sum_{s=1}^{R}T_{sr}^{1-\sigma}g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)}\frac{\partial \ln L_s^M}{\partial \ln w_x} \\
& +\frac{(\sigma-1)}{\sigma}\sum_{s=1}^{R}\frac{T_{sr}^{1-\sigma}g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)}{\sum_{s=1}^{R}T_{sr}^{1-\sigma}g_s^{\sigma-1}\left(w_s L_s^M + L_s^A\right)}\frac{\partial \ln g_s}{\partial \ln w_x}, \qquad (11)
\end{aligned}
$$

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

After defining

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

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

$$
\frac{\partial \ln w_r}{\partial \ln w_x} = \frac{1}{\sigma}\left(f_{rx}^{y} + \sum_{s=1}^{R} f_{rs}^{y}\frac{\partial \ln L_s^M}{\partial \ln w_x} + \sum_{s=1}^{R} f_{rs}^{g}\frac{\partial \ln g_s}{\partial \ln w_x}\right), \qquad (12)
$$

The terms on the right-hand side of (12) represent all the interdependencies between regional wages through trade or migration featured by the Krugman model. The first term, f_{rx}^{y}, represents a pure (nominal) income effect that works through trade between regions x and r. A positive wage shock in region x will, ceteris paribus, allow firms in region r to pay higher wages because it raises aggregate income in x, and thus nominal demand by consumers in x for the varieties produced in r. This direct income effect will be the higher, the larger f_{rx}^{y}, the share of the demand by manufacturing workers from region x in the real market potential of region r. The second term, $\sum_{s=1}^{R} f_{rs}^{y}\partial \ln L_s^M/\partial \ln w_x$, is an indirect income effect that works through interregional migration. A positive wage shock in region x will, ceteris paribus, allow firms in r to pay higher wages, if it induces net migration of workers, and thus income, toward r's main sales markets. This indirect income effect will be the higher, the more workers are induced by the shock to migrate to those regions that account for large shares of region r's sales. $\partial \ln L_s^M/\partial \ln w_x$ ($\lesseqgtr 0$) is the elasticity of employment in region s with respect to the wage rate in region x, which will be parameterized below, and f_{rs}^{y} the share of the demand by manufacturing workers from region s in the real market potential of region r. The third term, $\sum_{s=1}^{R} f_{rs}^{g}\partial \ln g_s/\partial \ln w_x$, finally, represents a price index (or competition) effect that works through both trade and migration. A positive wage shock in region x will, ceteris paribus, allow firms in region r to pay higher wages, if it enhances their competitiveness by raising the production costs of their main competitors disproportionately, thereby diverting demand toward the varieties produced in r. More precisely, the shock will allow firms in region r to pay higher wages, if it raises the CPIs in r's main sales markets disproportionately, i.e., if $\partial \ln g_s / \partial \ln w_x$ ($\lesseqgtr 0$), the elasticity of the CPI in region s with respect to the wage rate in region x, is positive for those regions s that feature high values of f^g_{rs}, their shares in region r's real market potential. As will be shown below, the bilateral CPI elasticity $\partial \ln g_s / \partial \ln w_x$ will be positive, if region s is hit by the wage shock itself ($s = x$), or if a shock elsewhere induces net out-migration of workers from those regions that account for high shares in region s's CPI.

Since the shares f^y_{rs} and f^g_{rs} are independent of values from region x, we can write equation (12) in matrix notation as

$$\mathbf{J}^w = \left(\frac{\partial \ln w_r}{\partial \ln w_x} \right)_{(R \times R)} = \frac{1}{\sigma} \left[\mathbf{f}^y + \mathbf{f}^y \mathbf{J}^L + \mathbf{f}^g \mathbf{J}^g \right], \tag{13}$$

where $\mathbf{f}^y = (f^y_{rs})_{(R \times R)}$ and $\mathbf{f}^g = (f^g_{rs})_{(R \times R)}$ are $(R \times R)$ matrices that depend on the parameters and equilibrium values of the endogenous variables of the Krugman model. In the empirical illustration below, we will assume these parameters and equilibrium values to be exogenous. The $(R \times R)$ matrices $\mathbf{J}^g = (\partial \ln g_r / \partial \ln w_x)_{(R \times R)}$ and $\mathbf{J}^L = \left(\partial \ln L^M_r / \partial \ln w_x \right)_{(R \times R)}$ will be parameterized in the next two steps by using the linearized equilibrium conditions (6) – (8).

To parameterize $\mathbf{J}^g$, the R^2 bilateral elasticities of the regional CPIs with respect to regional wages, we differentiate the linearized equilibrium condition for the price index (6) for all pairs of regions r and x.This gives

$$\begin{aligned} \frac{\partial \ln g_r}{\partial \ln w_x} = & \frac{T_{rx}^{1-\sigma} w_x^{1-\sigma} L_x^M}{\sum_{s=1}^R T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M} \\ & + \frac{1}{1-\sigma} \sum_{s=1}^R \frac{T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M}{\sum_{s=1}^R T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M} \frac{\partial \ln L_s^M}{\partial \ln w_x}, \end{aligned} \tag{14}$$

$r, x = 1, ..., R$. After defining, for any pair of regions r and x,

$$c_{rx} := \frac{T_{rx}^{1-\sigma} w_x^{1-\sigma} L_x^M}{\sum_{s=1}^R T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M} \geq 0, \tag{15}$$

which is the share of varieties from region x in region r's CPI, (14) can be expressed more compactly as

$$\frac{\partial \ln g_r}{\partial \ln w_x} = c_{rx} + \frac{1}{1-\sigma} \sum_{s=1}^R c_{rs} \frac{\partial \ln L_s^M}{\partial \ln w_x}, \tag{16}$$

or, in matrix notation, as

$$\mathbf{J}^g = \mathbf{c}^g + \frac{1}{1-\sigma}\mathbf{c}^g\mathbf{J}^L, \tag{17}$$

where $\mathbf{c}^g = (c_{rs})_{(R\times R)}$. The elasticity of the CPI in region r with respect to the wage rate in region x depends on two terms. The first term, c_{rx}, represents a direct price index effect. A positive wage shock in x will, ceteris paribus, increase production costs in x and thus sales prices for all varieties from this region. The CPI in region r will consequently increase the more, the higher the share of varieties from x in this CPI. The second term in (16), $(1-\sigma)^{-1}\sum_{s=1}^{R} c_{rs}\partial \ln L_s^M/\partial \ln w_x$, represents additional price index effects induced by interregional migration. A positive wage shock in region x will, ceteris paribus, increase the CPI in region r, if it induces workers to migrate from r or its neighbors to more distant regions, or, more precisely, if it induces net out-migration from those regions s that account for high shares in r's CPI to those that account for lower shares.[8] This out-migration will reduce the number of varieties produced at short distances from r.

Finally, to parameterize $\mathbf{J}^L$, the R^2 elasticities of manufacturing employment with respect to wages, we interpret the $(R-1)$ independent equations (7) together with (8) 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_r from (6), into equation (7), this system of equation is given by

$$\begin{aligned} 0 &= -\ln w_r + \ln w_i \\ &\quad + \frac{\mu}{1-\sigma}\left(\ln\left[\sum_{s=1}^{R} T_{rs}^{1-\sigma} w_s^{1-\sigma} L_s^M\right] - \ln\left[\sum_{s=1}^{R} T_{is}^{1-\sigma} w_s^{1-\sigma} L_s^M\right]\right), \quad (18) \\ 0 &= -\ln L^M + \ln\left(\sum_{s=1}^{R} L_s^M\right), \quad (19) \end{aligned}$$

where $r = 1, ..., i-1, i+1, ..., R$. This system of R equations implicitly determines equilibrium manufacturing employment in each region, $L_1^M, .., L_R^M$, as a function of the wages in all regions, $w_1, ..., w_R$. We can thus differentiate (18) and (19) separately for each pair of regions r and x and solve for $\mathbf{J}^L$. The derivatives of (18) are

[8] Notice that $1/(1-\sigma) < 0$.

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

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 (19) is $0 = L^{-1} \sum_{s=1}^R \partial \ln L_s^M / \partial \ln w_x$. Using the notation in (15), this system of equations can be expressed as

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

or, in a more compact form, as

$$
0 = \mu c_{rx}^L + \frac{\mu}{1-\sigma} \sum_{s=1}^R b_{rs}^L \frac{\partial \ln L_s^M}{\partial \ln w_x}, \tag{20}
$$

or, in matrix notation, as

$$
\mathbf{0}_{R\times R} = \mu \mathbf{c}^L + \frac{\mu}{1-\sigma} \mathbf{B}^L \mathbf{J}^L. \tag{21}
$$

$\mathbf{0}_{R\times R}$ is an $(R \times R)$ matrix of zeroes. 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 (21) for $\mathbf{J}^L$, which yields

$$\mathbf{J}^L = (\sigma - 1)\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L, \tag{22}$$

The term c^L_{rx} ($\lesseqgtr 0$) in (20) represents the extent to which the direct price index effects of the wage shock in region x (see variable c_{rx} in 15) distorts equality of real wages between region r and the reference region i for a given regional distribution of employment. c^L_{rx} will be positive, if the direct price index effect is larger (raises the CPI by more) in r than that i, i.e., if the real wage rate in r falls below that in the reference region i.[9] The term $\sum_{s=1}^{R} b^L_{rs} \partial \ln L^M_s / \partial \ln w_x$ ($\lesseqgtr 0$) represents the effects of the migration needed to restore real wage equalization between regions r and i. If the real wage rate in r falls below that in the reference region ($c^L_{rx} > 0$), migration must be such that it reduces the CPI, or increases nominal wages by more in r than in i. More workers must, ceteris paribus, migrate to r or its main suppliers than to i or its main suppliers.

By substituting (22) and (17) into (13), and assuming $\mathbf{c}^L$, $\mathbf{c}^g$ and $\mathbf{B}^L$ to be exogenous, we have now fully parameterized the bilateral wage elasticities (13) in terms of exogenous variables. The matrix $\mathbf{J}^w$ now reads

$$\mathbf{J}^w = \frac{1}{\sigma}\left[\mathbf{f}^y + (\sigma - 1)\,\mathbf{f}^y\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L + \mathbf{f}^g\left(\mathbf{c}^g + \mathbf{c}^g\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L\right)\right]. \tag{23}$$

After extracting $1/\sigma$, which will be the parameter to be estimated in the empirical illustration below, out of the matrix $\mathbf{J}^w$ and adding an error term, $\boldsymbol{\varepsilon}$, which accounts for Taylor approximation errors, to (10), the empirical SAR(1) model to be estimated is

$$\ln \mathbf{w} - \ln \widetilde{\mathbf{w}} = \frac{1}{\sigma}\left[\mathbf{W}\left(\sigma, \mu, \mathbf{T}, \mathbf{L}^A, \widetilde{\mathbf{w}}, \widetilde{\mathbf{L}^M}\right)\right](\ln \mathbf{w} - \ln \widetilde{\mathbf{w}}) + \boldsymbol{\varepsilon}, \tag{24}$$

where

$$\mathbf{W} := \sigma \mathbf{J}^w = \mathbf{f}^y + (\sigma - 1)\,\mathbf{f}^y\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L + \mathbf{f}^g\mathbf{c}^g + \mathbf{f}^g\mathbf{c}^g\left(\mathbf{B}^L\right)^{-1}\mathbf{c}^L \tag{25}$$

is the spatial weights matrix that summarizes all the R^2 bilateral regional wage elasticities. These weights represent all the interdependencies between regional wages featured by the Krugman model.

- The matrix $\mathbf{f}^y$ (≥ 0) represents direct nominal income effects. A positive wage shock in one region will, ceteris paribus, increase demand by this region for manufacturing varieties from all regions.

[9] The wage shock reduces this effect, if it hits region r itself ($\psi_r = 1$), and adds to this effect, if it hits the reference region ($\psi_i = 1$).

- The matrix $(\sigma - 1)\, \mathbf{f}^y \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L$ ($\lesseqgtr 0$) represents indirect, migration-induced income effects. A wage shock in one region will, ceteris paribus, induce interregional migration of workers that will change the spatial distribution of nominal demand for manufacturing varieties.

- The matrix $\mathbf{f}^g \mathbf{c}^g$ (≥ 0) represents direct price index effects. A positive wage shock in one region will, ceteris paribus, increase production costs in this regions and divert demand for manufacturing varieties to producers from other regions.

- The matrix $\mathbf{f}^g \mathbf{c}^g \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L$ ($\lesseqgtr 0$), finally, represents indirect, migration-induced price index effects. A positive wage shock in one region will, ceteris paribus, induce interregional migration of workers that will change the spatial distribution of the supply of manufacturing varieties.

3.2 Restricted models

The SAR(1) model (24) with spatial weights (25) represents the full Krugman model. It features simultaneously all four effects introduced in the previous subsection. We will henceforth refer to this model as model 0, or "full" model, and denote the corresponding spatial weights matrix (25) by $\mathbf{W}_0$,

$$\mathbf{W}_0 = \mathbf{f}^y + (\sigma - 1)\, \mathbf{f}^y \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L + \mathbf{f}^g \mathbf{c}^g + \mathbf{f}^g \mathbf{c}^g \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L. \tag{26}$$

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

In addition to testing the full Krugman model, we can test each of the four effects introduced above by comparing the empirical performance of the full model to the performances of restricted Krugman models where the effects to be tested are "switched off". Since the restrictions affect only the spatial weights, we can map the restricted models into SAR(1) models in the same way as the full model and estimate them in the same way.

The first restriction we impose on the full Krugman model is switching off the two price index effects by fixing all consumer prices, and thus the CPIs in all regions, at their equilibrium values. With $\mathbf{J}^g = \mathbf{0}_{(R \times R)}$, the spatial weights matrix (25) simplifies to

$$\mathbf{W}_1 = \mathbf{f}^y + (\sigma - 1)\, \mathbf{f}^y \left(\mathbf{B}^L\right)^{-1} \mathbf{c}^L. \tag{27}$$

The SAR(1) model with $\mathbf{W} = \mathbf{W}_1$ will be labeled model 1. This model represents a partial equilibrium of the Krugman model in the presence of fixed prices but regionally mobile labor. Local wage shocks are assumed to propagate across regions only through the two income effects.

The second restriction is switching of the two migration-induced effects by fixing the regional distribution of manufacturing workers at its equilibrium, i.e., prohibiting interregional migration in response to real wage differences. With $\mathbf{J}^L = \mathbf{0}_{(R\times R)}$, the spatial weights matrix (25) simplifies to

$$\mathbf{W}_2 = \mathbf{f}^y + \mathbf{f}^g \mathbf{c}^g. \tag{28}$$

The empirical model (24) with $\mathbf{W} = \mathbf{W}_2$ will be labeled model 2. It represents a general equilibrium of the Krugman model in the presence of immobile labor but flexible prices. Local wage shocks are assumed to propagate across regions only through the direct income and price index effects.

The third restriction combines the previous two restrictions by switching off all price index and migration-induced effects. With $\mathbf{J}^g = \mathbf{J}^L = \mathbf{0}_{(R\times R)}$, the spatial weights matrix (25) simplifies to

$$\mathbf{W}_3 = \mathbf{f}^y. \tag{29}$$

The empirical model (24) with $\mathbf{W} = \mathbf{W}_3$ will be labeled model 3. It represents a partial equilibrium of the Krugman model in the presence of immobile labor and fixed prices. Local wage shocks are assumed to propagate across regions only through the direct income effect.

Finally, the fourth restriction is switching off all four effects featured by the Krugman model. We implement this restriction by conditioning the spatial weights on geographic distances only. We set

$$\mathbf{W}_4 = \mathbf{T}, \tag{30}$$

where the $(R \times R)$ matrix $\mathbf{T}$ is the matrix of interregional transport costs (T_{rs}). The empirical model (24) with $\mathbf{W} = \mathbf{W}_4$ will be labeled model 4. This model is theoryless. It is not informative about any economic forces shaping the regional distribution of wages. Notice that the 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.

4 Empirical illustration

This section illustrates the approach proposed in this paper by estimating the SAR(1) models derived from the unrestricted and restricted Krugman models for a panel of 3,076 mainland US counties 1990–2005. The section introduces the detailed regression model, proposes an iterative estimation strategy, explains how the variables and spatial weights are quantified, addresses endogeneity of the regressors, introduces the spatial J test for model evaluation, and, finally, presents the estimation results.

4.1 Regression model

The core econometric model to be estimated is based on (24), which is a SAR(1) model in the deviations of regional wages from their equilibrium values. Exploiting the panel structure of our data, this model reads:

$$u_{rt} = \rho \sum_{x=1}^{R} \omega_{rx} u_{xt} + \varepsilon_{rt}, \tag{31}$$

$r, x = 1, ..., R$, $t = 1, ...T$, where

$$\begin{aligned} u_{rt} &= \ln w_{rt} - \ln \widetilde{w}_r, \\ \omega_{rx} &= \sigma \frac{\partial \ln w_r}{\partial \ln w_x} \left(\widetilde{\mathbf{w}}, \widetilde{\mathbf{L}}^M, \mathbf{L}^A, \mathbf{T}, \sigma, \mu \right), \\ \rho &= 1/\sigma. \end{aligned} \tag{32}$$

u_{rt} is the annual deviation of the logged wage rate in region r at time t, $\ln w_{rt}$, from its equilibrium value, $\ln \widetilde{w}_r$, which we assume to be stable over time. ρ is a regression parameter that, for the NEG-based models $0-3$, depends inversely on the substitution elasticity, σ. ω_{rx} is a bilateral spatial weight, given by the (r, x)-th element of one of the five spatial weights matrices $\mathbf{W}_0 - \mathbf{W}_4$ introduced in the previous section. For the NEG-based models $0-3$, this weight is a nonlinear function of all the variables and parameters of the NEG model, which are the vectors of equilibrium wage rates, $\widetilde{\mathbf{w}}$, equilibrium manufacturing employment, $\widetilde{\mathbf{L}}^M$, and exogenous agricultural employment, $\mathbf{L}^A$, the matrix of bilateral interregional transport costs, $\mathbf{T}$, the substitution elasticity, σ, and the expenditure share for the manufacturing good, μ. For the theoryless model 4, the weights depends only on the matrix of bilateral interregional transport costs.

We extend (31) by adding a serially lagged dependent variable, u_{rt-1}, to eliminate past wage shocks. Mion (2004) and Head and Mayer (2006) show that wage shocks typically do not exhaust within a single year. We allow for this sluggishness in wage adjustments by specifying a partial adjustment process in the deviations of the regional wages from their equilibrium values,

$$u_{rt} = (1-\theta)\, \rho \sum_{x=1}^{R} \omega_{rx} u_{xt} + \theta u_{rt-1} + \varepsilon_{rt}, \tag{33}$$

where the parameter θ $(0 \leq \theta \leq 1)$ measures the sluggishness of wage adjustments. Stacking (33) over regions for each time period gives, in matrix notation,

$$\mathbf{u}_t = (1-\theta)\, \rho \mathbf{W} \mathbf{u}_t + \theta \mathbf{u}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{34}$$

which is the model we estimate in this paper for all five spatial weights matrices $\mathbf{W}_0 - \mathbf{W}_4$.

4.2 Estimation strategy

Estimation aims at identifying equilibria of the (full or restricted) Krugman model for predetermined values of $\widetilde{\mathbf{w}}$, $\widetilde{\mathbf{L}}^M$, $\mathbf{L}^A$, $\mathbf{T}$ and μ. An equilibrium of the Krugman model is characterized by the SAR(1) model (34) where the estimate of σ, henceforth denoted $\widehat{\sigma}\,(= 1/\widehat{\rho})$, is equal to its value used to calculate the spatial weights, $\overline{\sigma}$. This fixpoint for σ closes the linearized Krugman model. We follow Fingleton (2006) in searching for the fixpoints for σ by a two-step procedure. In the first step, we do a grid search over theoretically consistent and plausible values of σ (see Section 4.3 below). We calculate the spatial weights matrix for each grid value $\overline{\sigma}$, and estimate (34) for each of these matrices to obtain the corresponding estimates $\widehat{\sigma}$. In the second step, we refine the grid between those grid points that are closest to potential fixpoints. We perform an iterative line search between those neighboring grid points that exhibit opposite signs of the difference $\widehat{\sigma}-\overline{\sigma}$.[10] This line search is continued until our convergence criterion for fixpoints, $|\widehat{\sigma} - \overline{\sigma}| < 0.001$, is met. If there exists no fixpoint within the range of theoretically consistent and plausible values of $\overline{\sigma}$, we conclude that the respective (restricted or unrestricted) Krugman model does not fit the data. The existence of several fixpoints indicates multiple equilibria of the Krugman model.

Notice that the substitution elasticity acts, similar to the transport costs, like a trade impediment in NEG models. The higher the elasticity of substitution between local and imported varieties, the less regions trade with each other because consumers can more easily substitute local for imported varieties.[11] In our spatial weights matrix, this lower trade intensity shows up in terms of a higher ratio of intra- to interregional wage elasticities, ω_{rr}/ω_{rx}, $r \neq x$. As σ goes to infinity, the spatial weights matrix converges to the identity matrix, in which case the SAR(1) model becomes tautological. It explains regional wages perfectly by themselves.[12]

Because the spatial weights matrix converges to the identity matrix as σ or τ increase, σ and τ must be bounded from above in the estimation of the SAR(1) model (34). Unconstrained estimations would always yield extremely high values of σ or τ because higher values of σ or τ improve the objective function, i.e., reduce the sum of squared residuals or increase the likelihood. Notice that, following Hanson (2005), virtually all previous estimations of NEG models escape this need to constrain parameters by setting the main diagonal

[10] In each iteration of this line search, we choose a new $\overline{\sigma}$ between the two values of $\overline{\sigma}$ with opposite signs of $(\widehat{\sigma} - \overline{\sigma})$, calculate the spatial weights matrix for this new $\overline{\sigma}$, and reestimate (34) to obtain the estimate $\widehat{\sigma}$ associated with this $\overline{\sigma}$.

[11] This is why the term $T_{rx}^{1-\sigma}$ is frequently used as a measure of (inverse) trade freeness.

[12] More precisely, $\lim_{\sigma\to\infty} \mathbf{W}_k\,(\sigma, ...) = \sigma \mathbf{I}_R$, where $\mathbf{I}_R$ is an $(R \times R)$ identity matrix and $k = 0, 1, 2, 3$ indexes NEG-based models. Figures A2 and A3 and Tables A1 – A3 in Appendix 1 illustrate this. They show for selected models and parameter sets that the main diagonal elements tend to increase relative to the off diagonal elements as σ increases. The effects of wage shocks predicted by the respective NEG model become more localized as a consequence.

of the transport cost matrix to zero. This constraint is unnecessarily restrictive in our view. Implying that consumers spend all their income on imported varieties, it drives a wedge between empirics and theory that may invalidate interpretation of the regression results on the backdrop of the NEG model. In contrast to these studies, we allow the NEG model to determine the intensity of intraregional trade but constrain the values of σ and τ, as will be detailed in the next subsection.

4.3 Quantification of regressors

Estimation of (34) requires quantification of the unknown vectors of equilibrium wage rates, $\widetilde{\mathbf{w}}$, equilibrium manufacturing employment, $\widetilde{\mathbf{L}}^M$, and exogenous agricultural employment, $\mathbf{L}^A$, the matrix of bilateral interregional transport costs, $\mathbf{T}$, as well as the substitution elasticity, σ, and the the expenditure share for manufacturing goods, μ. Our estimation strategy requires that all these variables or parameters are exogenous and fixed.

We estimate (34) using annual data for 3,076 counties in the 48 mainland US states and Washington, DC., for the period 1990–2005. The US meets the assumptions of NEG models fairly well. It features a large and highly integrated domestic market where trade and migration are not impeded notably by border impediments or infrastructure deficits. Our choice of annual data implies that we evaluate the NEG model by means of short-term responses to local wage shocks. Still, since workers are more mobile in the US than in many other developed countries (Obstfeld and Peri 1998), at least some of the indirect, migration-induced effects hypothesized by the Krugman model should show up in the data, if the model is correct. The sample period of 16 years is long enough to limit the effects of outliers, and short enough to justify our assumption that the US economy is characterized by a single, time-invariant equilibrium (see below).

We approximate equilibrium regional wages, $\widetilde{w}_r$, which enter both the dependent variable and the spatial weights, by averages over the sample period of the observed regional wages.[13] This approximation assumes that the equilibrium of the US economy was stable during the whole period under study, 1990–2005. While it is used frequently for macroeconomic models, this approximation may be problematic for NEG models that are characterized by multiple equilibria and

[13] We calculate the observed regional wage rates 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.

path dependency. However, we find no indication of switches between equilibria in our sample dataset.[14] To eliminate national trends, inflation and business cycle fluctuations from the observed data, we demean the observed wages by their contemporary national averages. Formally, we measure annual wages, w_{rt} in (32), by $w_{rt} = w_{rt}^{obs} - \left(\Pi_{r=1}^{R} w_{rt}^{obs}\right)^{1/R}$, and approximate equilibrium wages by $\widetilde{w}_r = \left(\Pi_{t=1}^{T} w_{rt}\right)^{1/T}$. The superscript "$obs$" indicates observed values. The advantage of using geometric rather than arithmetic averages of the wage rates is that it eliminates any region-specific effects from the dependent variable. It relieves us from adding region-fixed effects to the model, which would further complicate the estimation. Taken together, our dependent variable is akin to within transformed logged regional wages (Baltagi 1995: 28),

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

In line with the approximation of the equilibrium regional wages, we approximate equilibrium regional employment in manufacturing, $\widetilde{\mathbf{L}}^M$, and exogenous regional employment in agriculture, $\mathbf{L}^A$, by the long-run geometric averages over the sample period, i.e., by $\widetilde{\mathbf{L}^M} = \left(\Pi_{t=1}^{T} \mathbf{L}_t^M\right)^{1/T}$ and $\mathbf{L}^A = \left(\Pi_{t=1}^{T} \mathbf{L}_t^A\right)^{1/T}$, respectively. We take the immobile, agricultural employment of the Krugman model to comprise all employment in Agriculture, Natural Resources and Mining (1011), Construction (1012), Education and Health Services (1025) and Public Administration (1028).[15] These sectors account for about 30% of the employment in the US on average over the period under study. Broadly in line with the choice of "agricultural" sectors, we set the income share spent on agricultural goods, $1-\mu$, to 0.5. This is approximately the share of food (1992: 14.3%), alcoholic beverages (1%), tobacco products and smoking supplies (0.9%), housing (31.8%), and education (1.4%) in average annual expenditures in the US during the period under study.[16] $\mu = 0.5$ implies that consumers spend half of their income on goods whose production is subject to increasing returns to scale.

For the bilateral transport costs, summarized in the matrix $\mathbf{T}$, we use inverse exponential distances, which are most closely related to iceberg transport

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[14] To test for switches between equilibria in our sample, we simulated the equilibrium distributions of wages and manufacturing employment across US counties from equations (1)–(4), using the observed annual data as start values. If the equilibrium of the US economy had switched, the model should have converged to different equilibria for different years. The model converged to the same equilibrium for all year from 1990–2005, however.

[15] We combine data on aggregate employment from the REIS with sectorally disaggregated employment data is from the Quarterly Census of Employment and Wages (QCEW) published by the Bureau of Labor Statistics. To reduce the mismatches between the REIS and QCEW data, we calculate employment in the manufacturing 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 REIS, and $l_{r,QCEW}^A$ the share of our agricultural sector in total employment from the QCEW.

[16] 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.

costs.[17] More specifically, we parametrize the weights for any regions r and x by $T_{rx} = \exp(\tau D_{rx})$ where D_{rx} is the Euclidean distance between the centroids of counties r and x,[18] and τ the distance decay parameter. We set intraregional transport costs to zero, which implies that the main diagonal of $\mathbf{W}_4$ is zero while the main diagonals of all NEG-based spatial weights matrices $\mathbf{W}_0 - \mathbf{W}_3$ are nonzero. We set $\tau = 0.03$ in our baseline estimations. For this value, which implies that 22% of the iceberg is still left after 50 miles (5% after 100 miles), the theoryless model turns out to fit the data best, according to the R^2. In addition to this, our results for $\tau = 0.03$ are, by and large, representative for a wide range of values of the transport cost parameter. To illustrate the robustness of our results, we also report the results for various other distance decay parameters ranging from 0.005 to 0.1. At $\tau = 0.005$, 60% of the iceberg are still left after 100 miles. At $\tau = 0.1$, only 0.00005% are left.

The substitution elasticity, σ, finally, must be bounded from both below and above in the NEG-based models. The lower bound is, for the models with mobile workers, 0 and 1, given by the so-called "no black hole condition", $\sigma(1 - \mu) > 1$ (see Fujita et al. 1999: 59). This condition ensures that dispersion equilibria are possible at all. With our choice of $\mu = 0.5$, all values of $\sigma > 2$ meet the no black hole condition. For the models with immobile workers, 2 and 3, the lower bound for σ is one. The upper bound is needed to rule out equilibria that imply autarchy of all regions, as discussed in the previous subsection. We set this upper bound to 10 for all four NEG-based models. Test regressions for selected higher values of σ yielded no additional insights.

4.4 Endogeneity

We assume the serially lagged dependent variable, $\mathbf{u}_{t-1}$, to be weakly exogenous. This assumption appears to be not too restrictive in a model that identifies parameters from variations in temporary shocks. Since any region-specific effects are eliminated from the data by the construction of the dependent variable, there is no need to take first differences of (34) that would make the serial lag endogenous.

The spatially lagged dependent variable, $\mathbf{W}\mathbf{u}_t$, must be considered endogenous due to reverse causality, by contrast. In addition to spillovers of wage shocks from region x to region r, the parameter ρ may pick up contemporaneous spillovers in the opposite direction. We address this endogeneity by resorting

[17] We use the same specification of the transport costs for all models 0 – 4. In contrast to most of the empirical literature, we prefer the exponential over the power function (D_{rs}^{τ}, see, e.g., Behrens et al. 2009b) because the latter is inconsistent with the iceberg concept. The power function converges to infinity rather than to one with decreasing distance.

[18] The coordinates of the counties' centroids are from Rick King's dataset at http://home.comcast.net/~rickking04/ gis/spcmeta.htm.

to the GMM instruments suggested by Kapoor et al. (2007). Kapoor et al. suggest constructing instruments from the reduced form of the regression model at hand. Solving (34) for $\mathbf{u}_t$ gives, under the usual regularity conditions,

$$\begin{aligned}\mathbf{u}_t &= \left(\mathbf{I}_R - (1-\theta)\,\rho\mathbf{W}\right)^{-1}\left[\theta\mathbf{u}_{t-1} + \boldsymbol{\varepsilon}_t\right] \\ &= \sum_{m=0}^{\infty}\left[(1-\theta)\,\rho\mathbf{W}\right]^m\left[\theta\mathbf{u}_{t-1} + \boldsymbol{\varepsilon}_t\right]. \qquad (35)\end{aligned}$$

Feasible instruments for $\mathbf{u}_t$ thus include $\mathbf{W}^m\mathbf{u}_{t-1}$, which are the first and higher-order spatial lags of the serial lag $\mathbf{u}_{t-1}$. We use its first two spatial lags, $\mathbf{W}\mathbf{u}_{t-1}$ and $\mathbf{W}^2\mathbf{u}_{t-1}$ along with $\mathbf{u}_{t-1}$ as instruments, and estimate (34) by two-stage least squares (2SLS).

While this instrumentation strategy is feasible from a formal point of view, it may not succeed in perfectly eliminating all sources of endogeneity. The parameter ρ should ideally be identified only from those shocks that do actually originate from region x in year t but not from those that originate from third regions, or from those that hit several regions simultaneously. ρ may, for example, be biased by sector-specific shocks that affect regions simultaneously but with different intensity, depending on the regions' sectoral specializations. ρ should also be identified only from those channels of interregional shock transmission that are actually addressed by NEG. In addition to trade and migration, commuting, knowledge spillovers, or collaboration between firms may serve as channels of interregional shock transmission that are not addressed by NEG. ρ may be biased, if wage shocks propagate through these omitted channels in similar ways as through trade and migration. We doubt, however, that our estimates of ρ, and thus of the substitution elasticity σ, are subject to serious endogeneity biases. The spatial lag, $\mathbf{W}\mathbf{u}_t$, is a fairly complex product of many individual spatial weights, which in turn, are shaped in very specific ways by the general equilibrium of the NEG model. Even if some of the direct interdependencies between regional wages predicted by the NEG model coincide with the interdependencies predicted by other theories, the indirect, general equilibrium interdependencies are unlikely to coincide with the predictions of those theories as well. In fact, Francis and Zheng (2012) suggest that the main inferences drawn from estimations of NEG-based wage equations are fairly robust to such endogeneity biases. They eliminate potential sources of these biases from the wages by first estimating a Mincer-type wage regression for micro data, and using only the region fixed effects of this regression as wages in their NEG-based model. In Appendix 2, we check for possible biases of our main results by using filtered regional wages that are net of skill premia. Our main results go through although the point estimates differ somewhat and are less precise.

4.5 Model evaluation

Having estimated the unrestricted and restricted NEG-based models $0-3$ as well as the theoryless model 4, one would wish to test formally which of the models fits the data best. In addition to this, one may wish to compare different fixpoints identified for the same model to each other to decide which of the equilibria fits the data best. Direct comparisons of the R^2's or likelihoods of the fixpoint regressions are not informative because the regression models are not nested, and because the fit statistics tend to decrease (SSR) or increase (R^2, likelihood) with decreasing trade freeness (increasing σ or τ), as noted in Section 4.2.

We use the spatial J test (Kelejian and Piras 2011a, 2011b) to test models or equilibria against each other. In a nutshell, the spatial J test is based on the estimation of a benchmark model, which is assumed to be the true model under the null hypothesis, extended by the predicted value of the dependent variable from an alternative model, which is assumed to be the true model under the alternative hypothesis. The null hypothesis is rejected against the alternative, if the parameter of the predicted value differs significantly from zero by means of an χ^2 or t test. Spatial J tests have generally been shown to have fairly high power for discriminating between different spatial weights matrices (Piras and Lozano-Gracia 2012), provided these weights matrices are not too similar to each other. Moreover, spatial J tests are fairly easy to calculate. We note, however, that the spatial J test will tend to favor the model with lower trade freeness (lower σ or τ; see Section 4.2). There is still need for future research on developing more reliable statistical tests for the comparison of models estimated by the approach proposed in this paper.

4.6 Results

This section presents and discusses the results of the empirical illustration of the approach proposed in this paper. Table 1 reports the results for the baseline specifications of the NEG-based models 0–3 where we set the transport cost parameter at $\tau = 0.03$. It also presents the results for the theoryless model 4 with $\tau = 0.03$. This transport cost parameter generates the highest R^2 for model 4 (see Figure A1 in Appendix 1). For the four NEG-based models, each column of Table 1 reports the results of one regression that represents an equilibrium of the respective model in the sense that it meets our criterion for a fixpoint, $|\widehat{\sigma} - \overline{\sigma}| < 0.001$. The search procedure for identifying these fixpoints is described in Section 4.2. The upper panel of Table 1 reports the predetermined values of the parameters used to calculate the spatial weights matrices $\mathbf{W}_0 - \mathbf{W}_4$ (equations 26 – 30) prior to the estimations, the middle panel the parameters estimated from the SAR(1) model (34) by linear 2SLS, and the lower panel diagnostic statistics. The estimated parameters are the spatial lag parameter ρ, the sluggishness parameter θ and the intercept. The estimate for the substitution elasticity is calculated as $\widehat{\sigma} = (1 - \widehat{\theta})/\widehat{\rho}$.[19] SHAC standard deviations are given

[19] We use the delta method to estimate the standard deviation of $\widehat{\sigma}$.

in parentheses.[20]

Table 1 here.

We identify two fixpoints for σ for each of the NEG-based models 0–3, which mirrors the fact that the Krugman model features multiple equilibria. For given spatial distributions of wages and employment ($\widetilde{\mathbf{w}}$ and $\widetilde{\mathbf{L}}^M$), the respective unrestricted or restricted NEG models are solved for two different parameter sets. One equilibrium is at around $\sigma = 2$, the second at higher values of $\sigma \approx 6$ (models 0 and 1) or $\sigma \approx 9$ (models 2 and 3). For model 0 (regionally mobile workers, flexible prices of the heterogeneous good) and model 1 (mobile workers, fixed prices), none of the two fixpoint values of σ differs significantly from zero at conventional error probabilities, however. This suggests that these equilibria are empirically irrelevant for the US in the period under study. The spatial lags, $\mathbf{W}_0\mathbf{u}_t$ and $\mathbf{W}_1\mathbf{u}_t$, do not contribute notably to explaining the regional variations of wage shocks in the US.[21] Our *first main result* is thus that the data obviously reject the full Krugman model. For models 2 (immobile workers, flexible prices) and 3 (immobile workers, fixed prices), the higher fixpoint estimates for $\sigma \approx 9$ are insignificant as well while the lower estimates for $\sigma \approx 2$ differ significantly from zero.[22] This suggests, on the one hand, that there is some support from the data for the way the Krugman model addresses trade in heterogeneous goods. On the other hand, it suggests that the inferential statistics for fixpoints may help in distinguishing empirically relevant from irrelevant equilibria.

By comparing the NEG-based models with each other, we may gain some additional information about why the data reject the full Krugman model (see Section 3.2). A comparison between models 0 and 2, which differ only in the assumption about worker mobility, suggests that the data reject the way the Krugman model addresses mobility of workers. An empirically relevant, statistically significant fixpoint exists for model 2 where workers are assumed to be immobile but not for model 0 where workers are assumed to be mobile. The same result arises from the comparison between models 1 and 3, which also

[20] These standard deviations are robust to spatial heteroscedasticity and spatial autocorrelation (SHAC). See Moscone and Tosetti (2012) who extend the SHAC estimators developed by Kelejian and Prucha (2007) to panel data. We use the Parzen kernel with a threshold distance of 13.42 miles. A region's error variance is smoothed across at most seven neighbors.

[21] For illustration, Figure A2 in Appendix 1 maps selected columns of the spatial weights matrices associated with the two fixpoints for model 0. The figure maps the elasticities of the wages in all US counties with respect to the wages in New York City, NY, Altlanta (Fulton county), GA, and Douglas county, SD. New York City and Altlanta exemplify metropolitan centers, Douglas county a rural region. The figure shows that the Krugman model predicts the effects of wage shocks to be more localized for higher values of σ. Tables A1–A3 in Appendix 1 additionally report the the five lowest and highest of the bilateral wage elasticities mapped in Figure A2.

[22] See Figure A2 and Tables A1–A3 in Appendix 1 for illustrations of the spatial weights in model 3 for $\tau = 0.03$. The fixpoint estimates at higher values of σ turn significant as well for higher values of τ, though, as will be shown below.

differ only in the assumption about worker mobility. This is our *second main result*: The Krugman model obviously doesn't get mobility of workers right.

There may be several reasons why the Krugman model doesn't get mobility of workers right in the present empirical framework. One reason may be that the time horizon of our empirical illustration is too short. Using annual data, we focus on short-term responses to wage shocks within one year. Workers who face significant migration cost may take more than one year to decide about moving to a different county.[23] Still, there should be at least some migration responses to wage shocks in the US even in the short run, which the SAR model would have picked up, if the Krugman model predicted the directions of this migration correctly. A second reason may be that the model doesn't get the migration incentives right. While it assumes that maximizing real wages is the only relevant decision parameter, migrants in the US have arguably increasingly cared about consumption amenities such as favorable climate (Glaeser and Tobio 2007, Rappaport 2007, 2008, Shapiro 2008). In addition to this, the model may exaggerate the multiplier effects on wages triggered by wage shocks because it puts too little emphasis on dispersion forces. As Tables A1 – A3 in Appendix 1 show, the equilibrium wage elasticities predicted by model 0 are much higher in absolute terms than those predicted by model 3. These elasticities would most likely be lower, if the model accounted for migration costs or agglomeration diseconomies (Bickenbach and Bode forthcoming). And a third reason may be that the Krugman model doesn't get the consequences of migration right. It may over- or understate the true local wage effects of out- or in-migration.

While the data reject the way the Krugman model addresses mobility of workers, they offer little discriminatory evidence on the way the Krugman model addresses price formation on the markets for the heterogeneous goods. The results for the models with fixed prices (2 and 3) are very similar to those of the corresponding models with flexible prices (0 and 1, respectively). This is our *third main result*: Changes in regional prices are apparently not among the major channels through which local wage shocks spill over across regions in the short run.

This leaves the direct income effect as the only effective, statistically significant channel for regional shock transmission in our framework. Model 3 suggests that a positive wage shock in one region will increase nominal demand from this region for varieties produced in neighboring regions, which, in turn,.will increase the wages in these neighboring regions. This result is broadly in line with the results of earlier studies such as Hanson (2005), Mion (2004) or Redding and

[23] In fact, several NEG-flavored empirical studies report evidence suggesting that migration patterns do, in the longer run, respond to changes in the market potential. Redding and Sturm (2008) observe significant migration away from the inner-German border after the division of Germany in the late 1940s. Several other studies, including Crozet (2004), Ottaviano and Pinelli (2006), Pons et al. (2007), and Paluzie et al. (2009), also report evidence on such a positive relationship between migration and market potentials in several European countries.

Venables (2004). However, even model 3 does not fit the data better than our theoryless benchmark model 4 where the regional diffusion of wage shocks is assumed to depend only on geography. Spatial J tests clearly suggest that neither model 3 nor any of the models 0 − 2 contributes significantly to explaining the variations in regional wages over and above model 4 (see Table 1, second-last row). This is our *fourth main result*: None of the NEG-based models we estimate fits the data better than the theoryless model. This result is in contrast to those of earlier studies that, following Hanson (2005), use the nominal market potential as a benchmark, which depends on geography and nominal GDP.

Among the other estimated parameters of the SAR(1) models, the partial adjustment parameter, θ, is estimated fairly precisely at around 0.75 (see Table 1) and is comfortably far away from the unit root. The estimates for this parameter vary only marginally across all the fixpoint regressions for models 0–3 and the regression for model 4. There is obviously considerable sluggishness in regional wage shocks that may, if not accounted for, bias the estimates of σ (resp. ρ). The R^2s are also remarkably similar across all regressions, including that for the theoryless model. In line with the spatial J tests, this suggests that the Krugman model generally does not contribute much to explaining the variations in regional wages.

To illustrate the search for fixpoints for σ in more detail, Figure 1 depicts, separately for each NEG-based model, the function $\widehat{\sigma} = f(\overline{\sigma})$ we identify empirically in the course of the search process. The fixpoints reported in Table 1 are given by the intersections of $\widehat{\sigma}$, the curve labeled "sigma hat (tau=0.03)", with the diagonal line ("sigma hat = sigma bar"). The figure shows that $\widehat{\sigma}$ is not only a highly nonlinear but also discontinuous function of $\overline{\sigma}$. The fixpoints are usually close to the points where the functions are discontinuous. $\widehat{\sigma}$ responds very sensitively to small changes of $\overline{\sigma}$ in the proximity of these discontinuity points. A coarse grid search over only a few values of $\overline{\sigma}$ may thus easily miss discontinuity points, and thus fixpoints.

Figure 1 here.

The four main results drawn from the baseline specifications with $\tau = 0.03$ also hold, by and large, for a wide range of values of τ. As a robustness check, we report the estimates for 20 different values of τ, ranging from 0.005 to 0.1 (steps of 0.005), for each of the four models 0–3. Figure 2 summarizes the results of these checks by plotting the point estimates of σ at all fixpoints for the various values of τ. Filled (black) dots represent fixpoint estimates for σ that differ significantly from zero (at 5% error probability or less), empty (white) dots represent fixpoint estimates that do not differ significantly from zero. For most of the 20 values of τ, we identify two fixpoints for each model. For the models with mobile labor, 0 and 1, $\widehat{\sigma}$ is not significant at any of these fixpoints. This corroborates the robustness of our first main result: The data obviously reject the full Krugman model. The two models with immobile labor, 2 and 3, by contrast, feature at least one significant fixpoint for each value of τ. This corroborates the robustness of our second main result: The Krugman model doesn't get mobility of workers right in the present empirical framework. For higher values of τ (model 2: $\tau \leq 0.06$, model 3: $\tau \leq 0.05$), models 2 and 3 feature even two significant fixpoints. These two respective fixpoints do not differ significantly from each other for any value of τ, however, according to spatial J tests. Figure 2 also indicates that the results for models 0 and 1 are very similar to each other. The same holds for models 2 and 3. Our third main result is thus robust as well: Regional prices are not among the major channels of regional shocks transmission in the short run. The robustness of our fourth main result, the failure of NEG-based models in fitting the data better than the theoryless model, is exemplified by the fact that not a single equilibrium of an NEG-based model we identify for the various values of τ comes even close to passing the spatial J test.[24]

Figure 2 here.

5 Conclusion

In this paper, we propose a new approach for testing nonlinear NEG models that assume regions to interact not only through trade but also through migration. Bringing a reduced form of an NEG model to the data that takes into account all equilibrium conditions of the model simultaneously, this approach accounts not only for direct relationships between the variables of the model but also for all the indirect, general equilibrium effects that make NEG models so rich. In addition to testing the NEG model as a whole, the approach also facilitates testing selected features of the model separately, such as the interdependencies between wages and the prices of the heterogeneous good, or those between wages and interregional migration. This should help in identifying where the theory warrants improvements in cases when the model as a whole fits the data poorly.

The approach maps all equilibrium conditions of a specific NEG model into bilateral elasticities of the wage rate in each region with respect to the wage rates in all regions. These bilateral elasticities, which predict how strongly the equilibrium wage rate in a region will, according to the underlying NEG model, respond to a local wage shock elsewhere, are embedded as spatial weights in a spatial autoregressive model of order one—SAR(1)—in the deviations of regional wages from their equilibrium values. Estimation of this SAR(1) model allows to assess how accurately the NEG model predicts the way wage shocks propagate across regions. If the wage elasticities predicted by the NEG model fit the data well, the NEG model has presumably something to contribute to explaining the spatial distribution of economic activity. By mapping the NEG model into

[24] The detailed test statistics, which are not reported here for the sake of brevity, are available from the authors upon request.

spatial weights, the approach not only exploits the natural complementarity between NEG and spatial econometrics but also provides a consistent foundation of spatial weights in economic theory.

We introduce the approach by mapping the standard multiregion Krugman model, taken right out of a textbook, into spatial weights, and illustrate it by estimating the resulting SAR(1) model for a panel of 3,076 US counties 1990–2005. Using annual data, this illustration focuses on the short-term responses to wage shocks. We find that the Krugman model as a whole does not fit the data. The SAR model with spatial weights derived from the full Krugman model does actually not contribute significantly to explaining the variations in regional wages. A SAR model with spatial weights derived from a restricted Krugman model where labor is assumed to be regionally immobile fits the data somewhat better, by contrast. This suggests that the Krugman model doesn't get the incentives for, or the consequences of, interregional migration right. It arguably puts too little emphasis on dispersion forces like agglomeration diseconomies or specific locational preferences of workers that have directed migration flows away from the highly agglomerated northeast of the US toward the less agglomerated south. The poor fit of the Krugman model as a whole does not result in the first place from inappropriate definition of regional price indices for the heterogeneous good, by contrast. SAR models with spatial weights derived from a restricted Krugman model where prices are assumed to be fixed fits the data similarly poorly (mobile labor) or well (immobile labor) as the corresponding SAR models for flexible prices. Prices for the heterogeneous good are apparently not among the major channel for interregional shock transmission in the US, according to this result.

Even the restricted Krugman model with immobile labor does, however, not fit the data better than a theoryless model where the interregional wage elasticities depend only on geography. This result seems to corroborate Krugman who argued recently that the forces NEG describes may be "waning rather than gathering strength" (Krugman 2009: 570). It is, however, too early for a final assessment of NEG. Additional rigorous tests of NEG models, most importantly of those models that put more emphasis on dispersion forces, are warranted. Using the approach proposed in this paper, these tests may also help discriminate empirically between the many different types of dispersion forces proposed in the theoretical literature (see Bickenbach and Bode forthcoming).

There is ample scope for extensions of the approach proposed in this paper and for refinements of the econometric analysis. The approach may be extended in order to exploit employment shocks in addition to wage shocks for the evaluation of NEG models. This extension requires mapping the NEG model into a system of two estimable interdependent equations, one equation for wage and one for employment shocks. In addition to exploiting the data more extensively, this extension will offer greater opportunities for testing individual elements of NEG models. The econometric analysis may be refined by exploring alternative ways of approximating equilibrium values of the endogenous variables of the NEG model. One alternative to the long-run averages of observed data we use may be simulated equilibrium values. Another refinement is devising an instrumentation strategy for the spatial lag that effectively eliminates joint regional shocks and regional interdependencies through commuting, knowledge spillovers or firm collaboration. The gains from this refinement in terms of bias reduction may be rather limited, though. A third refinement is expanding the periodicity of the empirical analysis from one to several years. Focusing on medium-term effects of wage shocks may help in capturing the consequences of interregional migration better.

Appendices

Appendix 1: Additional tables and figures

Tables A1 − A3 and **Figures A1 − A3** here.

Appendix 2: Regressions for wages net of skill premia

This appendix show that the main results of the empirical illustration in Section 4.6 are not driven entirely by regional differences in human-capital intensities or human-capital externalities. It reports estimation results for equation (34) where all regional wages (w_{rt}) that enter the regression variables or spatial weights are replaced by wages net of skill premia, denoted by $\widehat{w}_{rt}$. The regression model and the regression method are exactly the same as those discussed in Section 4.

We eliminate skill premia from the observed wages by a simple auxiliary panel OLS regression. We regress the observed wage rates on the 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,

$$w_{rt} = \alpha_1 h_{rt}^{bach} + \alpha_2 h_{rt}^{high} + \iota_t + \xi_{rt}, \tag{36}$$

and then calculate the filtered wage rates as

$$\widehat{w}_{rt} = \iota_t + \xi_{rt}. \tag{37}$$

The annual county-level shares of persons with a bachelor degree and a high school diploma in the total population aged 25 or more are taken from Bode (2011). The time dummies in (36) 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 for all counties and years for simplicity.

Figure A4, which has the same shape as Figure 2 in Section 4.6, plots the point estimates of all fixpoints for σ we identify for the net wages. In general, we identify less fixpoints for the models with filtered than for those with unfiltered wages. Multiple equilibria are the exception rather than the rule for the filtered wages. In addition to this, the parameter σ is generally estimated less precisely. Still, our main results are essentially the same.

1. *The full Krugman model doesn't fit the data.* For model 0, there is not a single fixpoint for σ where σ is estimated to differ significantly from zero (upper graph in Figure A4)

2. *The data reject the way the Krugman model addresses mobility of workers.* With filtered wages, this result holds true at least for the comparison of the two models with fixed prices with each other. Model 3, which assumes

workers to be immobile, features some significant fixpoints for σ while model 1, which assumes workers to be mobile, does not. The comparison of the two models with flexible prices offers no insights, by contrast, because none of these models features a significant fixpoint for σ.

3. *Changes in regional prices are not among the major channels through which local wage shocks propagate across regions in the short run.* While model 2, which assumes prices of the heterogeneous good to be fixed, features some significant fixpoints for σ, model 2, which assumes the prices to be flexible, does not.

4. *None of the NEG-based models fits the data better than the theoryless model.* Spatial J tests not reported here indicate that model 3, the only NEG-based model that features significant fixpoints for σ with filtered wages, does not contribute significantly to explaining the variations in regional wages over and above the theoryless model 4.

Figure A4 here.

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Table A1. Ranking of wage elasticities of US counties with respect to a wage shock in Atlana, GA, models 0 and 3, $\tau = 0.03$

Rank	County (FIPS)	ω_{rx}	Rank	County (FIPS)	ω_{rx}
	Model 0, $\sigma = 2.214$			Model 0, $\sigma = 6.729$	
1	Clayton,GA (13063)	0.546	1	Fulton,GA (13121)	3.941
2	Cobb,GA (13067)	0.539	2	Douglas,GA (13097)	2.197
3	DeKalb,GA (13089)	0.522	3	Cobb,GA (13067)	2.174
4	Henry,GA (13151)	0.473	4	DeKalb,GA (13089)	1.577
5	Rockdale,GA (13247)	0.463	5	Paulding,GA (13223)	1.534
⋮			⋮		
3076	Fulton,GA (13121)	–1.012	3076	Starr, TX (48427)	–0.001
	Model 3, $\sigma = 1.738$			Model 3, $\sigma = 9.016$	
1	Fulton,GA (13121)	0.299	1	Fulton,GA (13121)	0.836
2	Cobb,GA (13067)	0.248	2	Douglas,GA (13097)	0.374
3	Douglas,GA (13097)	0.242	3	Paulding,GA (13223)	0.157
4	DeKalb,GA (13089)	0.234	4	Cobb,GA (13067)	0.143
5	Clayton,GA (13063)	0.221	5	DeKalb,GA (13089)	0.095

Note: Largest (or smallest) entries of the columns for Fulton,GA, in the spatial weights matrices $\mathbf{W}_3$ or $\mathbf{W}_0$, respectively, for $\tau = 0.03$ and the fixpoint values of σ as given in the table.

Table A2. Ranking of wage elasticities of US counties with respect to a wage shock in New York city, NY, models 0 and 3, $\tau = 0.03$

Rank	County (FIPS)	ω_{rx}	Rank	County (FIPS)	ω_{rx}
	Model 0, $\sigma = 2.214$			Model 0, $\sigma = 6.729$	
1	Okanogan, WA (53047)	0.023	1	Eureka, NV (32011)	–0.000
⋮			⋮		
3072	Kings, NY (36047)	–5.671	3072	Queens, NY (36081)	–28.301
3073	Queens, NY (36081)	–5.673	3073	Hudson, NJ (34017)	–30.090
3074	Hudson, NJ (34017)	–5.697	3074	Kings, NY (36047)	–30.421
3075	Bronx, NY (36005)	–5.956	3075	Bronx, NY (36005)	–32.962
3076	New York, NY (36061)	–7.837	3076	New York, NY (36061)	–45.932
	Model 3, $\sigma = 1.738$			Model 3, $\sigma = 9.016$	
1	New York, NY (36061)	0.305	1	New York, NY (36061)	0.833
2	Hudson, NJ (34017)	0.277	2	Bronx, NY (36005)	0.618
3	Bronx, NY (36005)	0.274	3	Kings, NY (36047)	0.595
4	Kings, NY (36047)	0.269	4	Hudson, NJ (34017)	0.564
5	Queens, NY (36081)	0.267	5	Queens, NY (36081)	0.513

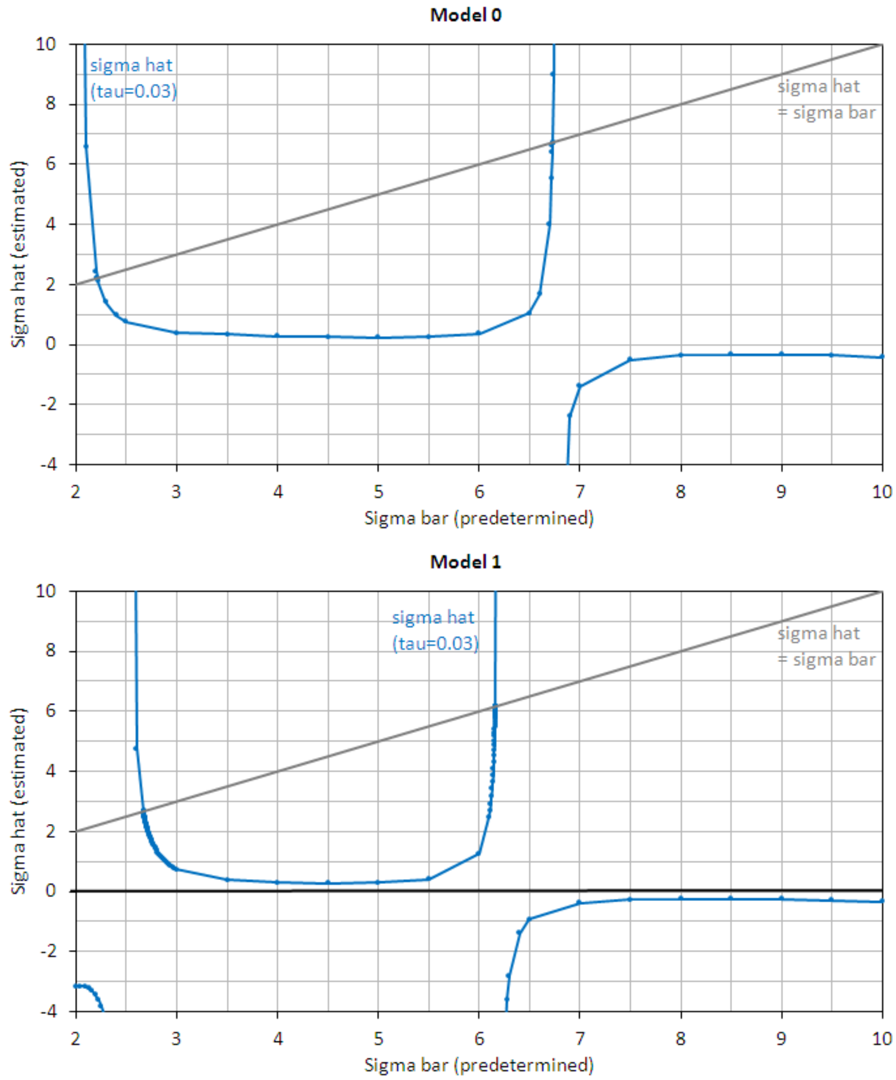
Note: Largest (or smallest) entries of the columns for New York city, NY, in the spatial weights matrices $\mathbf{W}_3$ or $\mathbf{W}_0$, respectively, for $\tau = 0.03$ and the fixpoint values of σ as given in the table.

Table A3. Ranking of wage elasticities of US counties with respect to a wage shock in Douglas, SD, models 0 and 3, $\tau = 0.03$

Rank	County (FIPS)	ω_{rx}	Rank	County (FIPS)	ω_{rx}
	Model 0, $\sigma = 2.214$			Model 0, $\sigma = 6.729$	
1	Douglas, SD (46043)	0.695	1	Douglas, SD (46043)	6.012
2	Aurora, SD (46003)	0.403	2	Charles Mix, SD (46023)	0.361
3	Boyd, NE (31015)	0.354	3	Aurora, SD (46003)	0.236
4	Davison, SD (46035)	0.353	4	Davison, SD (46035)	0.120
5	Gregory, SD (46053)	0.312	5	Hanson, SD (46061)	0.092
⋮			⋮		
3076	Douglas, SD (46043)	–0.839	3076	Starr, TX (48427)	–0.002
	Model 3, $\sigma = 1.738$			Model 3, $\sigma = 9.016$	
1	Douglas, SD (46043)	0.010	1	Douglas, SD (46043)	0.547
2	Charles Mix, SD (46023)	0.008	2	Charles Mix, SD (46023)	0.003
3	Aurora, SD (46003)	0.006	3	Aurora, SD (46003)	0.001
4	Davison, SD (46035)	0.006	4	Davison, SD (46035)	0.000
5	Boyd, NE (31015)	0.005	5	Hutchinson, SD (46067)	0.000

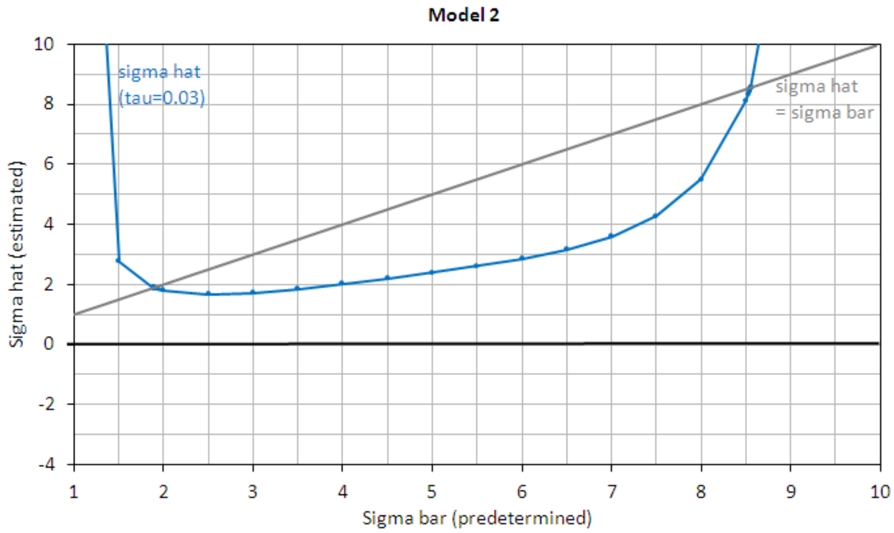
Note: Largest (or smallest) entries of the columns for New York city, NY, in the spatial weights matrices $\mathbf{W}_3$ or $\mathbf{W}_0$, respectively, for $\tau = 0.03$ and the fixpoint values of σ as given in the table.

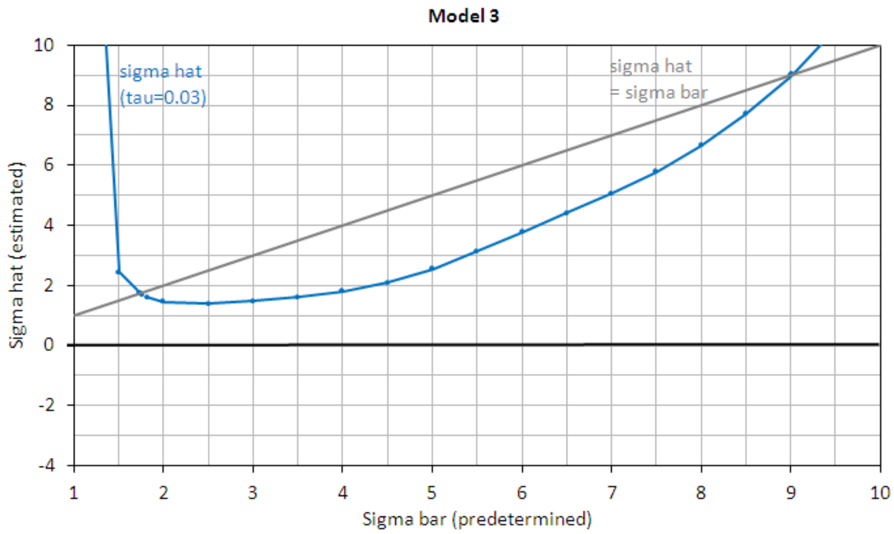
Figure 1. Search of fixpoints for substitution elasticity for models 0–3 and transport cost parameter $\tau = 0.03$: Predetermined and estimated values of the substitution elasticity



to be continued.

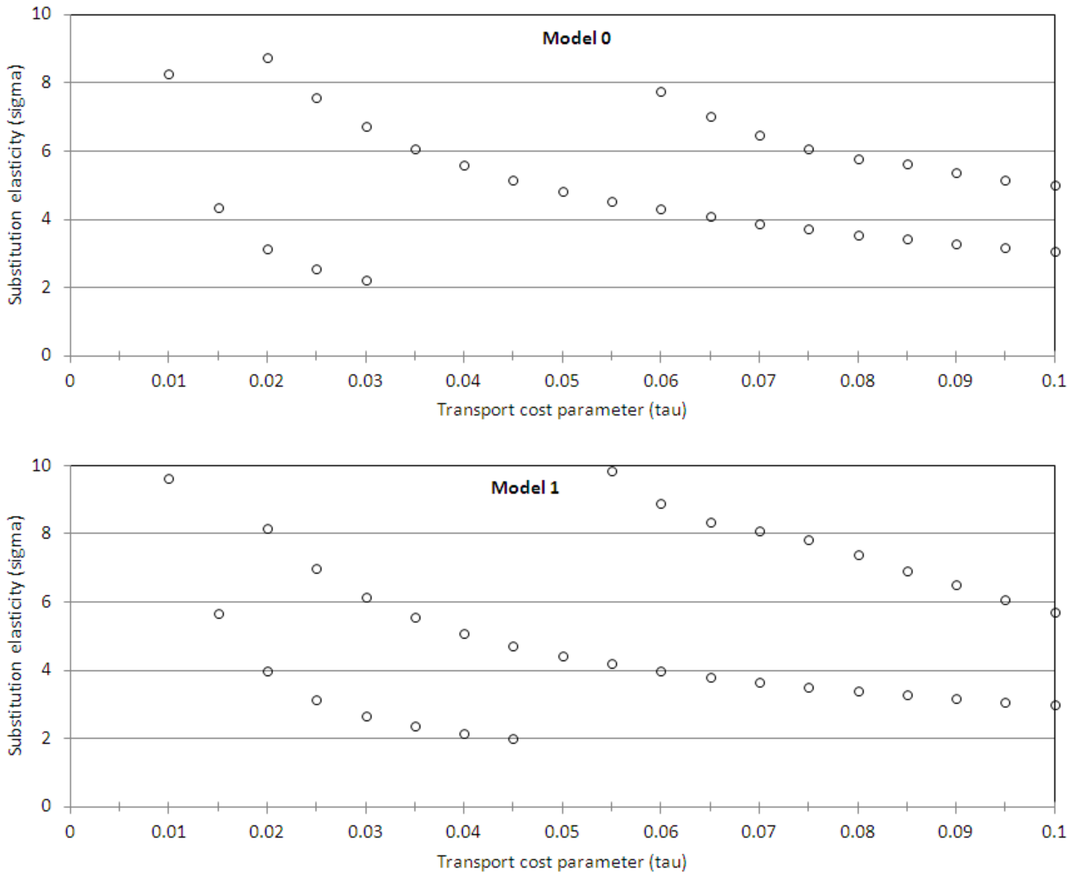
Figure 1 continued





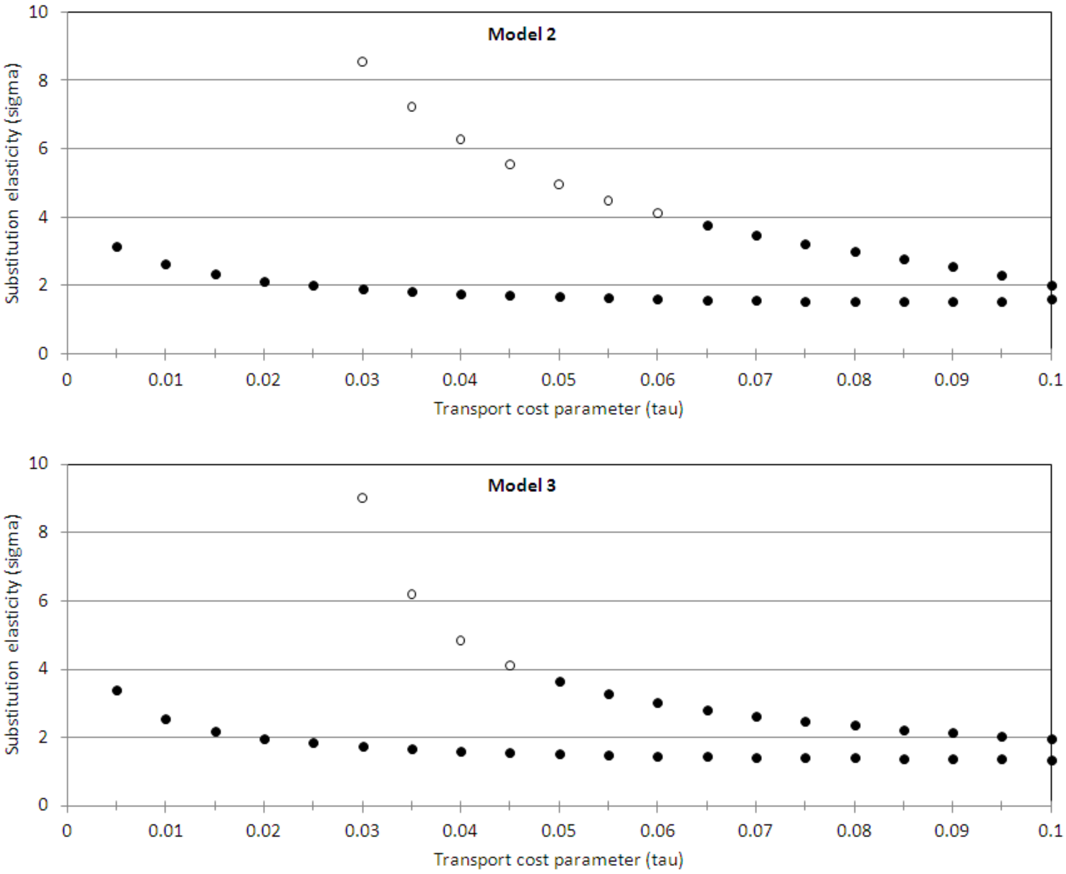
Notes: 2SLS regressions of SAR(1) model (34) with spatial weights $\mathbf{W}_0 - \mathbf{W}_3$ for panel of 3076 US counties 1990–2005 (46,140 observations). Each dot on the curves for "sigma hat (tau=0.03)" reports an estimate of the substitution elasticity $(\widehat{\sigma})$ for a separate predetermined spatial weights matrix $\mathbf{W}(\overline{\boldsymbol{\sigma}}, ...)$. "sigma hat = sigma bar": Possible loci of fixpoints for σ.

Figure 2. Fixpoints for substitution elasticity for models 0–3 and various values of the transport cost parameter: Point estimates and 90% confidence intervals for σ



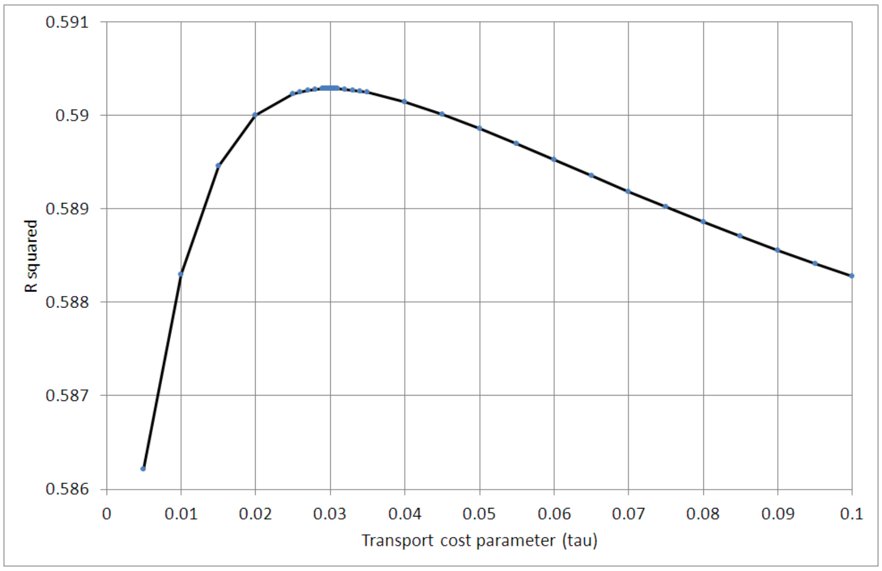
to be continued

Figure 2 continued



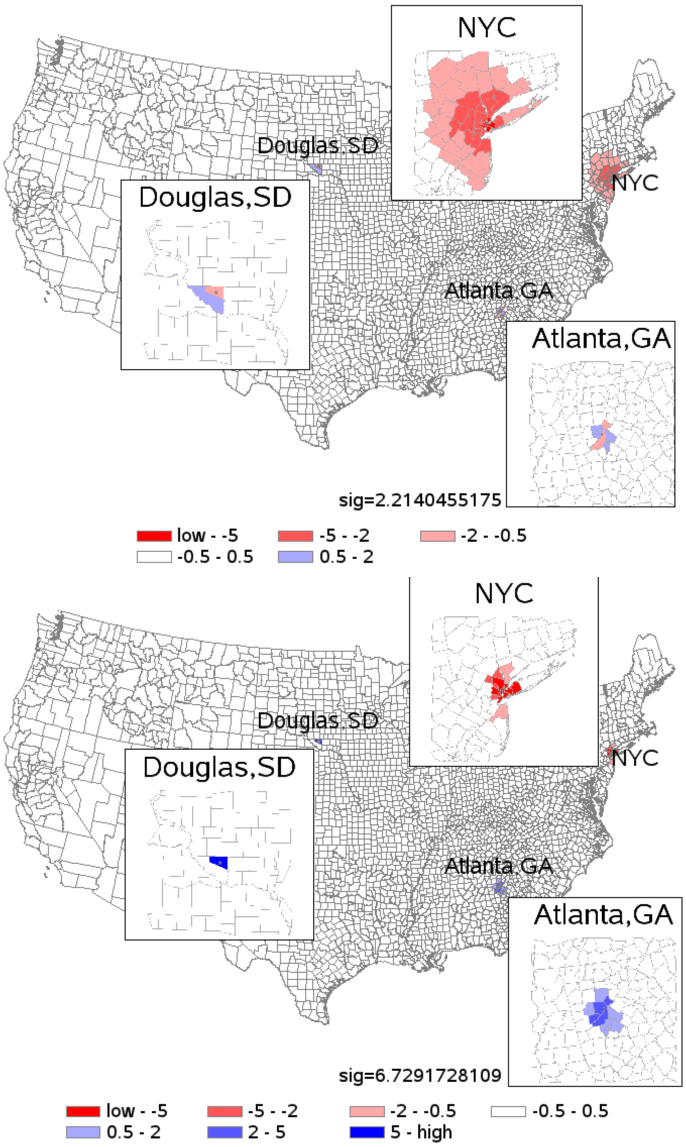
Notes: Each dot represents a fixpoint estimate for sigma. Black (white) dot: sigma is (not) statistically significant at 5% error probability. All estimates are from 2SLS regressions of SAR(1) model (34) with spatial weights $\mathbf{W}_0 - \mathbf{W}_3$, respectively, for panel of 3076 US counties 1990–2005 (46,140 observations) that meet the convergence criterion for fixpoints, σ, $|\widehat{\sigma} - \overline{\sigma}| < 0.001$ (see Section 4.2).

Figure A1. Fit of model 4 for various values of τ



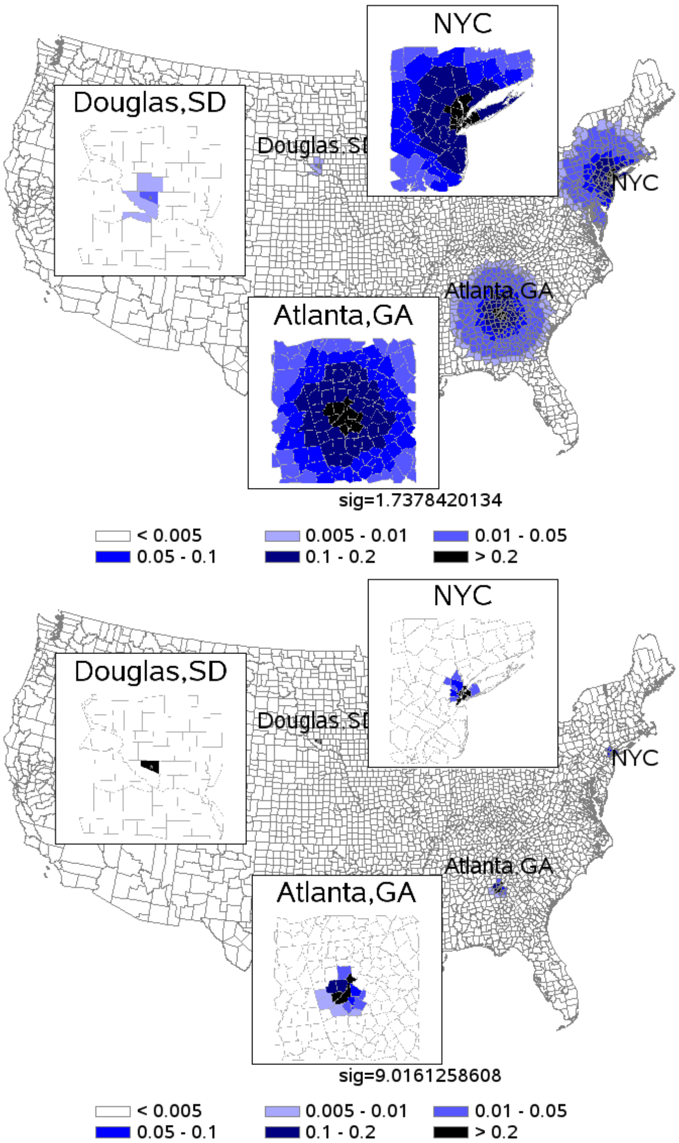
Notes: R^2s of 2SLS regressions of SAR(1) model (34) with spatial weights $\mathbf{W}_4$, calculated for different values of τ, for panel of 3076 US counties 1990–2005 (46,140 observations).

Figure A2. Wage elasticities in model 0 for $\tau = 0.03$: Wage shocks to New York city, NY, Atlanta,GA, and Douglas county, SD



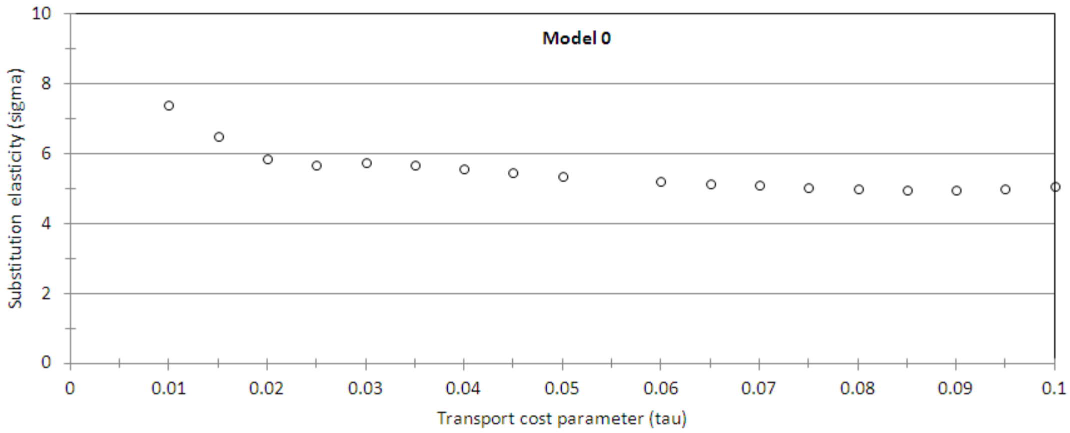
Note: Sum of the elasticities of the wage rate in the respective county to wage shocks in New York county, NY, Atlanta (Fulton county), GA, and Douglas county, SD.

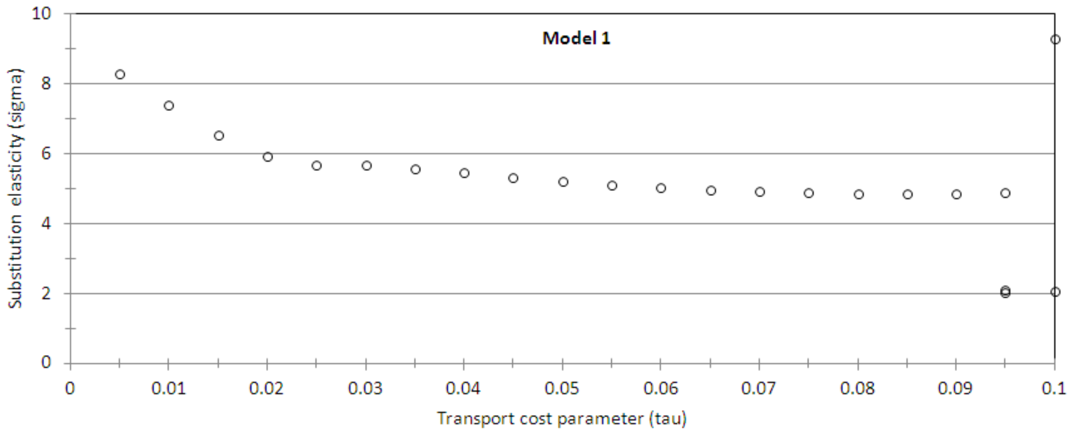
Figure A3. Wage elasticities in model 3 for $\tau = 0.03$: Wage shocks to New York city, NY, Atlanta,GA, and Douglas county, SD



Note: Sum of the elasticities of the wage rate in the respective county to wage shocks in New York county, NY, Atlanta (Fulton county), GA, and Douglas county, SD.

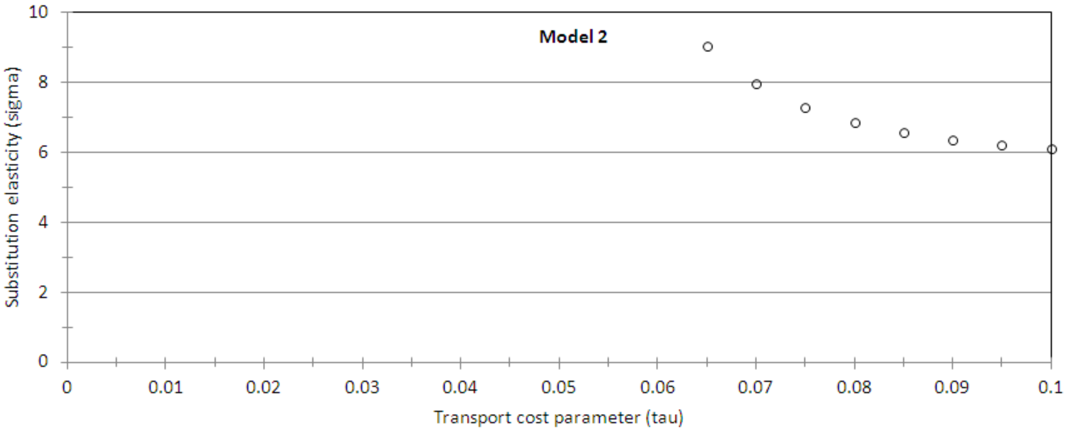
Figure A4. Robustness check for wages net of skill premia: Fixpoints for substitution elasticity for models 0–3 and various values of the transport cost parameter, point estimates and 90% confidence intervals for σ

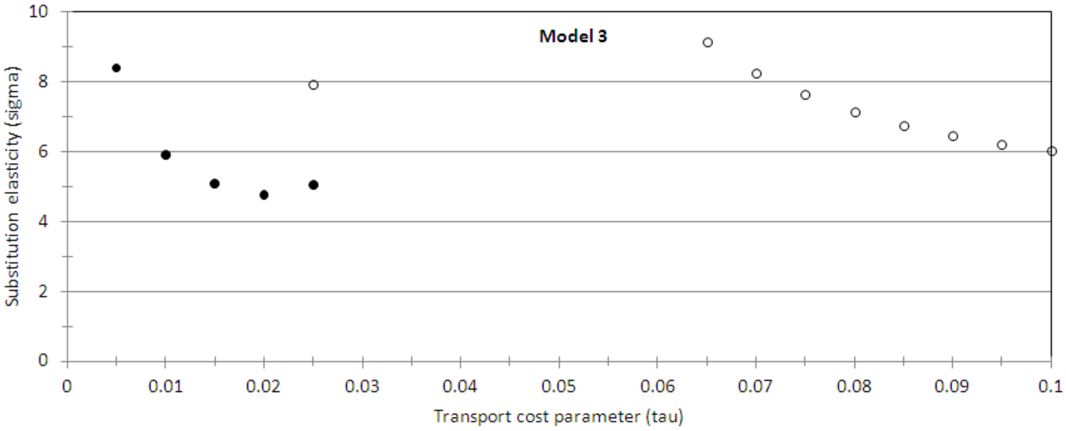




to be continued

Figure A4 continued





Notes: Each dot represents a fixpoint estimate for sigma. Black (white) dot: sigma is (not) statistically significant at 5% error probability. All estimates are from 2SLS regressions of SAR(1) model (34) with spatial weights $\mathbf{W}_0 - \mathbf{W}_3$ for panel of 3076 US counties 1990–2005 (46,140 observations) where the convergence criterion for fixpoints for σ, $|\widehat{\sigma} - \overline{\sigma}| < 0.001$, is met (see Section 4.2). All wages going into these regressions are net of skill premia, as described in the text.

Table 1. Regression results for models 0–4 and transport cost parameter $\tau = 0.03$

Model	0		1		2		3		4
	(full model)		(fixed prices)		(no migration)		(fixed prices, no migr.)		theoryless
				Parameters in spatial weights (predetermined)					
τ (transport costs)	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
μ (expend. share manuf.)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	—
$\overline{\sigma}$ (substitution elasticity)	2.214	6.729	2.671	6.164	1.887	8.555	1.738	9.016	—
				Parameter estimates					
$\widehat{\rho}$ (spatial lag)	0.111	0.037	0.092	0.040	0.140	0.031	0.152	0.029	0.121
	(0.102)	(0.974)	(0.161)	(1.025)	(0.016)	(0.048)	(0.016)	(0.057)	(0.018)
$\widehat{\theta}$ (partial adjustment)	0.754	0.752	0.754	0.752	0.737	0.732	0.736	0.736	0.738
	(0.007)	(0.010)	(0.006)	(0.007)	(0.009)	0.035	(0.009)	(0.029)	(0.010)
Intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Implied $\widehat{\sigma}(= 1/\widehat{\rho})$	2.213	6.729	2.670	6.163	1.886	8.554	1.738	9.015	—
	(2.001)	(177.1)	(4.675)	(156.9)	(0.172)	(11.91)	(0.149)	(16.57)	
R^2	0.578	0.582	0.578	0.582	0.592	0.604	0.592	0.598	0.590
Spatial J test (prob-value)									
H0: model 4	0.898	0.902	0.890	0.894	0.977	0.911	0.988	0.899	—
First stage R^2	0.582	0.582	0.582	0.582	0.584	0.582	0.584	0.582	0.583

Notes: 2SLS regressions of SAR(1) model (34) with spatial weights $\mathbf{W}_0 - \mathbf{W}_4$ for panel of 3076 US counties 1990–2005 (46,140 observations) that meet the convergence criterion for fixpoints for σ, $|\widehat{\sigma} - \overline{\sigma}| < 0.001$, is met (see Section 4.2). Spatial heteroscedasticity and autocorrelation consistent (SHAC) standard deviations in parentheses below the parameter estimates. "Parameters in spatial weights (predetermined)": Values of the structural parameters of the NEG model used to calculate the spatial weights $\mathbf{W}_0 - \mathbf{W}_4$ prior to the estimation."Parameter estimates": Values of parameters estimated from model (34) for given spatial weights $\mathbf{W}_0 - \mathbf{W}_4$. "Spatial J test (prob-value)": Prob value of spatial J tests of the theoryless model 4 (H0) against the respective Krugman model $(0 - 3)$ (H1).