Market Potential, Increasing Returns, and Geographic Concentration

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Abstract. In this paper, I examine the spatial correlation between wages and consumer purchasing power across U.S. counties to see whether regional demand linkages contribute to spatial agglomeration. First, I estimate a simple market-potential function, in which wages are associated with proximity to consumer markets. Second, I estimate an augmented market-potential function derived from the Krugman model of economic geography, parameter estimates for which reflect the importance of scale economies and transport costs. The estimation results suggest that demand linkages between regions are strong and growing over time, but quite limited in geographic scope.

JEL Classification: F12, R12.

Key words: Spatial agglomeration, market potential, increasing returns, transport costs.

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I. Introduction

In this paper, I examine changes in the spatial distribution of economic activity in the United States to see what they reveal about the strength of product-market linkages between regions. The starting point for the exercise is the idea that the level of economic activity in a location is conditioned by that location's access to markets for its goods. I attempt to show that market access – as opposed to the fixed characteristics of locations – provides a useful way to characterize the forces that contribute to the geographic concentration of economic activity.

There is a large theoretical literature on spatial agglomeration. Krugman (1991) explains city formation through the interaction of transport costs and firm-level scale economies.[1] Fujita, Krugman, and Venables (1999) show that in a broad class of models scale economies and transport costs combine to create spatial demand linkages that contribute to agglomeration. Firms are drawn to cities by the possibility of serving large local markets from a few plants at low transport cost. Congestion costs limit the degree of geographic concentration.

This idea is related to Harris' (1954) influential market-potential function, which states that the demand for goods produced in a location is the sum of purchasing power in other locations, weighted by transport costs. In its early form, the market-potential function was ad hoc. Fujita, Krugman, and Venables (1999) reinvigorate the market-potential concept by showing how it can be derived from formal spatial models. In its modern version, the market-potential function states that nominal wages are higher near concentrations of consumer and industrial demand.

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[1] This work builds on a large body of theoretical literature. See Fujita and Thisse (1996), Ottaviano and Puga (1997), and Fujita, Krugman, and Venables (1999) for surveys of previous research.

Recently, there has been a burst in empirical research on economic geography.[2] One strand of literature examines whether production or exports tend to concentrate near large national or regional markets, as would be consistent with Krugman's (1980) home-market effect (Davis and Weinstein 1999 and 2003; Head and Reis 2001; Hanson and Xiang 2004). A second strand examines how technology diffuses across space and how this in turn affects trade and industry location (Eaton and Kortum 1999 and 2002; Keller 2002). A third strand, and the one most related to this paper, examines whether incomes are higher in countries or regions with access to larger markets for their goods, as would be consistent with recent economic geography models (Hanson 1996 and 1997; Redding and Venables 2004; Head and Mayer 2004).[3]

To assess the importance of market access, I examine the spatial correlation of wages and consumer purchasing power across U.S. counties from 1970 to 1990. I first estimate Harris' market-potential function. In this specification, which resembles a spatial labor-demand function, nominal wages are increasing in consumer income in surrounding locations and decreasing in transport costs to these locations. The estimation results indicate how far demand linkages extend across space and how income shocks in one location affect other locations. I then estimate an augmented market-potential function, based on Helpman's (1998) extension of Krugman (1991). This specification, which nests the simple market-potential function, interacts consumer purchasing power with other variables and gives structural interpretations to the regression coefficients. The structural parameters reflect the magnitude of scale economies and transport costs.

This paper shares with Redding and Venables (2004) an estimation strategy that uses the

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2 See Head and Mayer (2003) and Overman, Redding, and Venables (2003) for surveys of this literature.

3 On spatial interactions see Eaton and Eckstein (1997), Eaton and Dekle (1999), and Dobkins and Ioannides (2001).

spatial variation in earnings to identify the structural parameters of a geography model. The two papers differ in several important respects. While Redding and Venables use cross-country data, I use cross-*county* data for a single country. Comparing my results to theirs allows one to see how the strength of spatial interactions changes as one moves from very small to very large geographic units. A second difference is that while their estimation uses data on cross-country trade flows, my analysis uses no trade data whatsoever.[4] This provides consistency check on the empirical application of geography models in that it shows how results change as we switch the basis for estimation from the spatial covariation in average incomes and trade flows (the RV approach) to the spatial covariation in wages and consumer purchasing power (my approach).

One problem for the empirical analysis is that the available measure of wages is average annual earnings per worker, which vary across locations in part because worker characteristics vary across locations. Cross-region variation in worker characteristics may reflect regional characteristics that are constant over the sample period, which can be removed by controlling for fixed location effects. Cross-region variation in worker characteristics may also reflect unobserved shocks to wages in a location that are correlated with changes in demand for locally produced goods, creating a possible source of simultaneity bias. I address this problem by instrumenting for changes in market potential using historical data on county population growth.

A second problem is that there are forces besides market access that contribute to spatial agglomeration. Agents may be drawn to regions with pleasant weather or other amenities (Roback 1982, Beeson and Eberts 1989). Additionally, human capital spillovers may make agglomerated regions attractive places to work (Rauch 1993; Black and Henderson 1999). To see how these

[4] A third difference is that Redding and Venables allow both households and firms to consume industrial products.

additional factors might influence the estimation, I compare results with and without controlling for local supplies of human capital and exogenous amenities. As this approach may not control for all factors behind geographic concentration, I address issues of interpretation in the text.

II. Theory

A. The Krugman Model

Recent theoretical work on economic geography attributes spatial agglomeration to product-market linkages between regions. A precursor to this approach is Harris' (1954) market-potential function, which equates the potential demand for goods and services produced in a location with that location's proximity to consumer markets, or

$$MP_j = \sum_{k \in K} Y_k e^{-d_{jk}} \tag{1}$$

where MP_j is the market potential for location j, Y_k is income in location k, and d_{jk} is distance between j and k. While early work simply asserted the existence of equation (1), recent theory derives a structural relationship similar to (1) from general-equilibrium spatial models.

I present the basic structure of the Krugman (1991) model, referring to Helpman's (1998) extension which is more tractable for empirical work.[5] All consumers have identical Cobb-Douglas preferences over two bundles of goods, traded (manufacturing) goods and housing services,

$$U = C_m^{\mu} C_h^{1-\mu} \tag{2}$$

[5] In Krugman (1991), there is an agricultural sector in place of the housing sector, where agricultural goods are produced under constant returns by immobile farm labor. The Helpman model, by introducing a nontraded good, generates a smoother, more realistic spatial distribution of production. See also Puga (1999).

μ is the share of expenditure on manufactures, C_h is the quantity of housing services consumed, and C_m is a composite of symmetric manufacturing product varieties given by

$$C_m = [\sum_i^n c_i^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \qquad (3)$$

where σ is the elasticity of substitution between any pair of varieties and n is the number of varieties. There are increasing returns in production of each manufacturing variety such that

$$L_{im} = a + bx_i \qquad (4)$$

where a and b are constants, L_{im} is labor used in variety i, and x_i is the quantity of i produced. In equilibrium each variety is produced by a single monopolistically competitive firm and the f.o.b. price for each variety is a constant markup over marginal cost, which depends on the wage, w.

There are J regions and L laborers, where laborers are perfectly mobile between regions. The stock of housing in region j is assumed to be fixed at H_j. Ownership of the housing stock is assumed to be symmetric across individuals such that each laborer owns share 1/L of the housing stock in each of the J regions. With iceberg transport costs in shipping goods between regions, the c.i.f. price of good i produced by region j and sold in region k is

$$P_{ijk} = P_{ij}\, e^{\tau d_{jk}} \qquad (5)$$

where P_{ij} is the f.o.b. price of good i produced in region j, τ is the unit transportation cost, and d_{jk} is the distance between j and k. The solution to the model is well known (Helpman 1998; Fujita, Krugman, and Venables 1999). For certain parameter values, manufacturing concentrates spatially. Firms desire to be in a region with high employment to serve a large local consumer market at low transport cost without duplicating fixed production costs. The costs of being in a large market are higher wages, resulting from high housing costs associated with local congestion.

To develop the intuition behind the market-potential function, it is useful to derive the demand for traded goods produced in some region j. Let C_{ijk} be the quantity of good i that region k purchases from region j. Given CES utility over traded goods, the symmetry of traded goods in technology and preferences, and the equilibrium condition on the constant markup of prices over marginal cost ($P_{ij} = \frac{\sigma}{\sigma-1} b w_j$), total sales of manufacturing goods by region j are

$$\sum_k \sum_i P_{ijk} C_{ijk} = n_j \sum_k \mu Y_k \left[\frac{\sigma}{\sigma-1} b w_j e^{\tau d_{jk}}\right]^{1-\sigma} T_k^{\sigma-1} \qquad (6)$$

where T_k is the CES price index for manufacturing goods available in region k. Under zero profits manufacturing sales in region j equal wages paid to labor in j. The wage bill in j thus equals $w_j n_j a\sigma$.[6] I then obtain a modified market-potential function (Fujita, Krugman, and Venables 1999),

$$w_j = \theta\left[\sum_k Y_k e^{-\tau(\sigma-1)d_{jk}} T_k^{\sigma-1}\right]^{1/\sigma} \qquad (7)$$

where θ is a function of fixed parameters. Wages in a location are increasing in the income of surrounding locations, decreasing in transport costs to these locations, and increasing the price of competing traded goods in these locations.

Following similar logic, the price index for traded goods in region j can be written as

$$T_j = \left[\sum_k n_k \left(\frac{\sigma}{\sigma-1} b w_k e^{\tau d_{jk}}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \qquad (8)$$

Equation (8) captures market equilibrium for traded goods. The price index for these goods is higher where a larger fraction of goods must be imported from distant locations.

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[6] The wage bill in region j equals $w_j L_{imj} n_j$, where L_{mj} is employment in production of manufacturing good i in j. By zero profits, which fixes $x=(\sigma-1)a/b$, and the symmetry in technology across regions, $L_{imj}=a\sigma$.

Beyond equations (7) and (8), there are three additional equilibrium conditions. Equilibrium condition three is that real wages are equalized across regions,

$$\frac{w_j}{P_j^{1-\mu} T_j^{\mu}} = \frac{w_k}{P_k^{1-\mu} T_k^{\mu}}, \quad \forall\, j \neq k \tag{9}$$

where P_j is the housing price in j. Equilibrium condition four is that regional income equals income derived from labor and housing,

$$Y_j = n_j w_j a\sigma + \frac{1-\mu}{\mu} \frac{n_j a\sigma}{L} \sum_k n_k w_k a\sigma, \quad \forall j \tag{10}$$

And equilibrium condition five is that housing payments equal housing expenditure,

$$P_j H_j = (1-\mu) Y_j, \forall\, j \tag{11}$$

By its simplicity, the Krugman model ignores many features of production and consumption which may influence industry location. My strategy is to examine whether such simple models are informative about the spatial distribution of economic activity.

B. Model Specification

Following the logic of new economic geography models, I make nominal wages the dependent variable. In the first specification, I apply Harris' market-potential function in (1) directly by relating nominal wages in a location to income in other locations, weighted by distance:

$$\log(w_{jt}) = \alpha_0 + \alpha_1 \log(\sum_k Y_{kt}\, e^{\alpha_2 d_{jk}}) + \varepsilon_{jt} \tag{12}$$

where t is the time period, w_{jt} is the nominal wage in region j, α_0, α_1, and α_2, are parameters to be estimated, and ε_{jt} is an error term discussed below. While (12) is not derived from an explicit model, its simplicity makes it a useful baseline model for assessing demand linkages between regions. In (12), wages in a location reflect the demand for goods produced in that location, where consumer demand is determined by transport costs and the spatial distribution of income.

The second specification I estimate is taken from the equilibrium conditions of the Krugman model, including the modified market-potential function in (7). Given limited spatial data on prices for traded goods (T_j), I cannot simultaneously estimate all of the model's structural equations. My approach is to derive an estimating equation by combining (7), (9), and (11), which yields the following augmented market-potential function:

$$\log(w_{jt}) = \beta + \sigma^{-1} \log(\sum_k Y_{kt}^{\frac{\sigma(\mu-1)+1}{\mu}} H_{kt}^{\frac{(\sigma-1)(1-\mu)}{\mu}} w_{kt}^{\frac{\sigma-1}{\mu}} e^{-\tau(\sigma-1)d_{jk}}) + \eta_{jt} \quad (13)$$

where β is a function of fixed parameters and η_{jt} is an error term discussed below. The parameters to be estimated are σ, the elasticity of substitution between traded goods (which we expect to exceed unity); μ, the expenditure share on traded goods (which we expect to be between zero and one); and τ, the transportation cost of shipping one unit of a good a unit distance (which we expect to be positive, such that transport costs are increasing in distance).

Equation (13) embodies three equilibrium conditions: the market-potential function in (7), real-wage equalization across regions in (9), and regional housing market equilibrium in (11). Since I do not incorporate two equilibrium conditions, equations (8) and (10), estimating (13) cannot be considered a full-information application of the Krugman model. Equation (13) differs from (12) by the inclusion of the price index for traded goods, which is

$$T_{kt}^{\sigma-1} = \gamma Y_{kt}^{\frac{(1-\sigma)(\mu-1)}{\mu}} H_{kt}^{\frac{(\sigma-1)(1-\mu)}{\mu}} w_{kt}^{\frac{\sigma-1}{\mu}}$$

where γ is a constant. The key difference, then, between (12) and (13) is that the latter controls for the regional variation in the price of traded goods while the former does not.

To interpret (13), note that for region j higher income in nearby regions raises demand for traded goods produced in j (as long as $\sigma(\mu-1)<1$), and higher wages in nearby regions raise the relative price of traded goods produced in these regions, which increases their demand for goods produced in j. Higher production of traded goods in j raises the region's demand for labor and its nominal wages and housing prices. Larger housing stocks in nearby regions imply lower housing prices and higher employment in these regions and so higher demand for traded goods.

III. Data and Estimation Issues

A. Data Sources

I take counties in the continental United States as the geographic unit of analysis. The data required are wages, employment, income, and housing stocks. County-level data on annual labor compensation and employment are available from the U.S. Bureau of Economic Analysis (BEA). The BEA tabulates both earnings and employment on a place of work basis. I use earnings and employment data for wage and salary workers. I measure income by total personal income, which is total income received by households and non-corporate businesses. I measure the housing stock as total housing units, from the U.S. Census of Population and Housing. The time period for the analysis is 1970, 1980, and 1990. Table 1 gives summary statistics on the variables.

B. The Spatial Distribution of Employment and Wages

In this section, I present data on wages and employment in U.S. counties. Wages are average annual earnings per worker for wage and salary workers. Employment is average annual employment of wage and salary workers per square kilometer. Variables are expressed relative to weighted averages for the continental United States.

As is well known, employment is spatially concentrated around cities and wages are relatively high near these areas of dense economic activity.[7] Employment densities in the most urbanized counties, which account for 5.4% of all counties, range from 6 to 2,237 times the U.S. average (in New York county). Surrounding major cities are regions with moderate employment densities, from 1.5 to 6 times the U.S. average. Over two-thirds of counties, mostly in farm and mountain states, have very low employment densities, only 0.2 to 0.6 times the U.S. average. That employment density declines as one moves away from large consumption masses is consistent with the idea that market access influences industry location.

Figure 1 shows the log change in county employment relative to the log change in U.S. employment for 1970-1990. Since 1970, there has been a sizable shift in employment from the northeast and midwest to the southeast and west, as discussed in Blanchard and Katz (1992). Interestingly, employment change in both high and low-growth regions is far from uniform. For instance, east and south Texas have high relative growth, but west and north Texas show relative declines, and while most counties in plains states have low relative growth, the Twin Cities region has high relative growth. As employment relocates to the south and west, it appears to concentrate in certain pockets, leaving other areas untouched.

Figure 2 shows the log change in county wages relative to the log change in U.S. wages between 1970 and 1990. Counties with high relative-wage growth are overwhelmingly concentrated in the southeast. Most counties in the northern midwest and the northeast, with the exception of the Atlantic seaboard, have relative-wage declines. Comparing Figures 1 and 2, the geographic expanse

[7] For the spatial density of U.S. employment and wage levels, see http://irpshome.ucsd.edu/faculty/gohanson/.

of relative-wage growth in the southeast appears to be larger than the geographic expanse of relative-employment growth in the region, suggesting that employment growth in high-activity counties puts upward pressure on wages in neighboring counties.

C. Estimation Issues

A first estimation issue relates to the geographic unit of analysis. More geographically disaggregated data reduces measurement error, but too much detail creates computational problems. The expressions in (12) and (13) are summed over all locations. Specifying the independent variables in (12) and (13) at the county level would create summation expressions with over 3,000 terms for each observation. Instead, I group surrounding counties within concentric distance bands and then aggregate the independent variables across counties within each band. For distances of 0 to 1000 km., the bands have a width of 100 km. (0-100 km., 100-200 km., etc.); for distances of 1000-2000 km. the bands have a width of 200 km.; and for distances above 2000 km. counties are treated as a single unit. I calculate the set of 16 concentric-ring aggregates for all counties in the sample. Distance to each aggregate is for the mid-point of the band.

A second estimation issue relates to heterogeneity in workers across regions. While the desired county wage measure is for a worker with some constant level of skill, the available wage measure is annual compensation per worker averaged across workers in a county. Let w_{jt} be the average wage in county j at time t and let w^*_{jt} be the constant-skill wage in county j. Variation in the constant skill wage, w^*_{jt}, across locations reflects true regional variation in nominal wages, due in theory to spatial variation in industry location. However, variation in country average wages, w_{jt}, may be due either to regional variation in w^*_{jt} or to regional variation in worker characteristics. To capture how measurement error in wages may affect the estimation, suppose that the deviation in the log average wage from the log constant-skill wage can be written as,

$$\log(w_{jt}) - \log(w^{*}_{jt}) = \omega_j + \nu_{jt} \tag{14}$$

The first component, ω_j, is the mean deviation between the county average and constant-skill wages, and the second component, ν_{jt}, is the period-specific deviation, assumed to be iid.

The mean deviation in wages may reflect regional differences that vary little over time, such as the availability of agricultural land, access to railroads and highways, the presence of universities, or proximity to state or national seats of government. If certain characteristics attract both industrial firms and more-skilled labor, then any correlation between wages and the market-potential index found in the data may be a byproduct of a correlation between the summation expressions in (12) and (13) and ω_j. For instance, university towns may have relatively large supplies of skilled workers (because college graduates tend to look for jobs near their place of education) and relatively large concentrations of production (because students and faculty are a captive local market). The temporal permanence of major population centers suggests that fixed regional characteristics are likely to be important in the location of economic activity. To remove the mean deviation in the average wage from the constant-skill wage from the estimation, I take time differences of the estimating equations, which produces the following specification for (13),

$$\begin{aligned}\Delta \log(w_j) = \sigma^{-1}[&\log(\sum_k Y_{kt}^{\frac{\sigma(\mu-1)+1}{\mu}} H_{kt}^{\frac{(\sigma-1)(\mu-1)}{\mu}} w_{kt}^{\frac{\sigma-1}{\mu}} e^{-\tau(\sigma-1)d_{jk}}) - \\ &\log(\sum_k Y_{kt-1}^{\frac{\sigma(\mu-1)+1}{\mu}} H_{kt-1}^{\frac{(\sigma-1)(\mu-1)}{\mu}} w_{kt-1}^{\frac{\sigma-1}{\mu}} e^{-\tau(\sigma-1)d_{jk}})] + \Delta\nu_{jt}\end{aligned} \quad . \tag{15}$$

The corresponding time-differenced expression for (12) is analogous.

The remaining error term, Δv_{jt}, is the change in the deviation of county average wages from county constant-skill wages. There may be concern that this error term is correlated with the change in the summation expression in (15). This would be the case, for instance, if counties that experience growth in demand for locally produced traded goods tend to attract workers with above average skills. To account for possible correlation between the error term and the change in the regressor function, I use a GMM estimator, in which I instrument for the regressor function using historical data on county population growth, where these values are lagged by ten years or more. In the estimation of equation (15) for the time period 1970-1980, the instruments I use are own-county and neighboring-county population growth over the periods 1930-1940, 1940-1950, and 1950-1960. Instruments for 1980-1990 are analogous. If county population growth reflects secular trends associated with long-run shifts in regional economic activity, then past growth rates for counties and their neighbors will help predict future growth in market potential.

A third estimation issue is that other factors that influence spatial agglomeration, such as supplies of exogenous amenities (e.g. Roback 1982) or localized human-capital externalities (e.g. Rauch 1993), may also influence the spatial distribution of nominal wages. I deal with this issue by including two sets of control variables in the estimation: changes in the shares of the working age population in a county by gender, age, and educational attainment; and indicators of exogenous amenities available in the county. An appendix describes the wage regressions. Following previous literature (e.g. Roback 1982), the measures of exogenous amenities I use are heating-degree days, cooling-degree days, average possible sunshine, average wind speed, average relative humidity, average precipitation, whether the county borders the sea coast, whether the county borders a great lake, and territorial water area in the county. By regressing county average wage growth on county education, the specification captures the impact of both individual education and average county education on wages, which implicitly controls for human-capital externalities across workers within a county (Rauch 1993). As many of the control variables are difficult to obtain for 1970, I include them in regressions for 1980 and 1990 only.

Other factors, such as technological spillovers, may also contribute to spatial agglomeration. One difficulty in controlling for this type of spillover is that it is possible to replicate some of the results of the Krugman model by replacing scale economies at the firm level with scale economies at the industry or region level, as would arise from spillovers between adjacent firms (Helpman 1998). Using external economies to explain spatial agglomeration has a long history in urban economics (Fujita and Thisse 1996). In these models, spillovers tend to be assumed rather than derived. Part of the appeal of the Krugman model is that pecuniary externalities arise endogenously. While spillovers between firms could certainly contribute to spatial agglomeration, the absence of microfoundations for this explanation perhaps makes it less compelling.

To summarize the estimation strategy, step one is to estimate a baseline, simple market-potential function in time-difference form. Step two is to estimate the augmented market-potential function based on the Krugman model in equation (15). This model nests the simple market-potential function, which permits a test of which model better fits the data.

IV. Estimation Results

The sample is 3,075 counties in the continental United States. The dependent variable in all specifications is the log change in average annual earnings for wage and salary workers. The independent variables are aggregates or averages across counties within concentric distance bands whose center is the county on which the observation is taken. All specifications are in time-differenced form for either 1970-1980 or 1980-1990. The base specification for the augmented market-potential function is equation (15), which written in reduced form is,

$$\Delta \log(w_j) = \alpha_0 + \alpha_1[\log(\sum_k Y_{kt}^{\alpha_3} w_{kt}^{\alpha_4} H_{kt}^{\alpha_5} e^{\alpha_2 d_{jk}}) - \log(\sum_k Y_{kt-1}^{\alpha_3} w_{kt-1}^{\alpha_4} H_{kt-1}^{\alpha_5} e^{\alpha_2 d_{jk}})] + \Delta\nu_{jt} \quad (15')$$

The variables in the regressor function are personal income (Y_k), distance in thousands of kilometers (d_{jk}), the housing stock (H_k), and average annual earnings for wage and salary workers (w_k). The base specification for the simple market-potential function is equation (15'), with the coefficient on income (α_3) constrained to be one and coefficients on wages (α_4) and housing stocks (α_5) constrained to be zero. I perform the estimation by either nonlinear least squares or GMM.

A. The Simple Market-Potential Function

Columns (1) and (2) of Table 2 show coefficient estimates for the simple market-potential function. The coefficient α_1 is the effect of the market-potential index on wages in a given county. Consistent with the market-access hypothesis, the coefficient is positive and precisely estimated in both time periods. Higher consumer demand appears to be associated with higher nominal wages in a given county. The coefficient α_2 is the effect of distance from consumer markets on wages in given county. Also consistent with the market-access hypothesis, the coefficient is negative and precisely estimated. Greater distance to consumer markets reduces nominal wages in a location. The effects of both market potential and distance appear to rise over time.

Table 2 also shows the sensitivity of the results to sample restrictions. I first examine whether the presence of high-population counties in the estimation affects the results. High-population counties, which are located in major urban areas, may be subject to greater measurement error in wages since urban areas tend to exhibit wider variation in worker skills. In columns (3) and (4) of Table 2, I exclude all counties with greater than 0.05% of the U.S. population. Coefficient estimates in columns (3) and (4) are very similar to those in columns (1) and (2).

The distance coefficients suggest that counties beyond 1000 km. carry a weight of zero in the estimation.[8] In columns (5) and (6) of Table 2, I redefine the summation expressions in equation (15) to exclude counties beyond 1000 km. from the county on which an observation is taken. The coefficient estimates in columns (5) and (6) are very similar to those in columns (1) and (2), suggesting that market potential is determined largely by economic activity in nearby regions. In unreported results, I found that estimation results are affected only when we begin to exclude counties within 800 km. of a given county.

Next, I examine the effects of adding controls for human capital and exogenous amenities. Columns (7)-(9) report regressions with these controls included for the 1980-90 time period. Coefficient estimates for these variables from the regression in column (7) are reported in an appendix. Comparing columns (7)-(9) with columns (2), (4), and (6), we see that while the coefficient on distance is unchanged by the addition of the control variables, the coefficient on the market-potential index falls in magnitude. This suggests market potential may be positively correlated with variables associated with higher average county wages, such as average education and experience. In other words, workers with higher observed levels of skill appear to be attracted to locations with strong consumer demand growth. This may help explain Rauch's (1993) finding that wages are higher in cities where average education is higher and Ciccone and Hall's (1996) finding that regional labor productivity is higher where the density of employment is higher.

[8] From column (1) of Table 2, the implied weight on income for a county 1000 kilometers away is $e^{-5.5}$=0.004.

In unreported results, I performed additional checks on the robustness of the findings. First, I estimated the simple market-potential function separately for eight geographic regions. This controls for western states, whose large land areas and low population densities may create differing regional demand linkages. Second, I estimated equation (17) using a more flexible specification of distance and transport costs. I replace the function $e^{\alpha d}$, which for negative α and positive d will be convex for all values of d, with the function $1/[1+(\rho d)^2]$, which depending on the value of ρ may have both convex and concave regions in d. Third, I aggregated counties by state rather than by concentric rings. These approaches all produce results that are similar to those in Tables 2 and 3.

For all specifications, α_1 and α_2 rise in absolute value over time, which suggests that the effects of both consumer purchasing power in other locations and distance to other locations have become more important. To help interpret the results, I calculate the predicted change in wages for a county associated with an increase in the county's market-potential index of 10%, where I assume that this increase in the index is concentrated at a single point in space. I then see how the predicted county wage change varies as we increase the distance of the point at which the shock is presumed to occur. Formally, the predicted wage change is given by,

$$\Delta \ln \hat{w} = \hat{\alpha}_1 \left[\ln\left((1 + 0.1 * e^{\hat{\alpha}_2 D}) \sum_k Y_k e^{\hat{\alpha}_2 d_k} \right) - \ln\left(\sum_k Y_k e^{\hat{\alpha}_2 d_k} \right) \right] = \hat{\alpha}_1 \ln(1 + 0.1 * e^{\hat{\alpha}_2 D}) \quad (16)$$

where $\Delta \ln \hat{w}$ is the predicted change in county wages, $\hat{\alpha}_1$ and $\hat{\alpha}_2$ are estimated coefficients, and D is the distance from a county to the location of the shock.

Figure 3a plots equation (16) using coefficient estimates from columns (1) and (2) of Table 2. The strength of local demand linkages appears to have increased over time. A nearby shock (within 8 km.) that increases the market-potential index by 10% increases wages by 2.6%, using coefficient estimates for 1970-1980 in column (1), and by 3.7%, using coefficient estimates for 1980-1990 in column (2). The impact of the shock falls off quickly with distance, and more so when using the 1980-1990 coefficients than when using the 1970-1980 coefficients. This suggests that importance of proximity to markets for wages has also increased over time.

These results on demand linkages between regions are roughly consistent with other work on the attenuation of agglomeration effects across space. Adams and Jaffe (1996) examine the correlation between a firm's R&D and productivity levels in the firm's outlying plants. While firm R&D is positively correlated with plant total factor productivity, this effect is much stronger for plants that are closer to the firm's R&D facilities. For plants beyond 100 miles of R&D labs, the effect of R&D on productivity is only 10-30% as strong.

To summarize the findings of this section, nominal wages are strongly, positively correlated with the distance-weighted sum of personal income in surrounding regions. These results are consistent with Harris' (1954) formulation of a market-potential function.

B. The Augmented Market-Potential Function

Table 3 reports nonlinear least squares estimation results for the augmented market-potential function in equation (15').[9] The dependent variable remains the log change in earnings of wage and salary workers. I report both the reduced-form regression coefficient estimates and the values of the structural parameters implied by these estimates.

Consider first the coefficient estimates in columns (1) and (2). It is again the case that

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[9] I impose restrictions on the reduced-form parameters implied by (15). Relaxing these restrictions slightly improves the fit of the regression. Structural parameters derived from the two sets of regressions are similar.

the coefficient on the market-potential index, α_1, is positive and precisely estimated and that the coefficient on distance, α_2, is negative and precisely estimated. In comparing these coefficient estimates to those for the simple market-potential function in Table 2, we see that in Table 3 the effect of market potential is smaller and the effect of distance is larger. The additional variables in the augmented market-potential function, the housing stock and wages, enter with positive exponents, and the exponent on total personal income is positive but smaller than unity. Comparing values of the Schwarz Criterion in Tables 2 and 3, we see that the augmented market-potential function improves the fit of the regression in all cases. Table 3 also reports the results of a Wald test on the hypothesis that the data support the coefficient constraints imposed by the simple market-potential function (i.e., that α_3 equals one and that α_4 and α_5 equal zero). I reject this hypothesis at any level of significance. The reduced-form effects of personal income, wages, and housing on market potential are broadly consistent with the Krugman model. Higher personal income, higher wages, and higher housing stocks in surrounding locations are all associated with higher wages in a given country.

Columns (3) and (4) of Table 3 report estimation results for low-population counties, which, as in Tables 2 and 3, are very similar to those for the full sample. Columns (5) and (6) report results including controls for human capital and exogenous amenities for the 1980-90 time period. These results are qualitatively similar to those without controls, though distance effects appear to be smaller in absolute value once additional controls are included in the regression. An appendix reports coefficient estimates on these variables for the regression in column (5).

Consider next to the structural parameters implied by the reduced-form coefficient estimates, which can be derived by comparing equations (15) and (15') (see note 17). Consistent with theory, estimates of σ, the elasticity of substitution, are greater than 1, and range in value between 4.9 and 7.6. This is roughly in line with other estimates of the elasticity of substitution based on gravity-type models of international trade (Head and Mayer 2003). Recent estimates of σ in the empirical literature are concentrated between 4.0 and 9.0 (e.g. Feenstra 1994, Head and Ries 2000). The lower is the value of σ, the lower in absolute value is the own-price elasticity of demand for any individual good and the more imperfectly competitive is the market for that good. By profit-maximization, $\sigma/(\sigma - 1)$ equals the ratio of price to marginal cost. The implied price-cost margins range from 1.15 to 1.25 and are precisely estimated in all cases. In equilibrium, price equals average cost, in which case a value of $\sigma/(\sigma - 1)$ greater than one indicates production of traded goods is subject to scale economies.

Also consistent with theory, estimates of μ, the expenditure share on traded goods, are between 0 and 1. However, with a mean expenditure share on housing in the United States of approximately 0.20, estimated values for μ of 0.91 to 0.97 may seem too high. This may suggest that the stark categorization of goods as either traded consumables or housing services is too restrictive. Estimated values of τ, unit transport costs, suggest, counterintuitively, that transportation costs have risen over time. However, it is difficult to evaluate the net effect of this change from the distance parameter alone, as other parameters also change over time. Below, I examine spatial decay functions implied by these coefficient estimates.

In Table 4, I re-estimate the regressions in columns (1), (3), and (5) of Table 3 by GMM. The instruments are lagged own-county log population growth and lagged values of log population growth in surrounding counting. Since the coefficient estimates are somewhat sensitive to the choice of instruments, I report two sets of estimates, one for a narrow set of instruments (lagged population growth in the own county and immediately surrounding counties) and another for a broader set of instruments (lagged population growth in the own county, immediately surrounding counties, and more-distant counties). Based on tests of overidentifying restrictions, in all regressions I fail to reject the hypothesis that the instruments are uncorrelated with the errors at conventional levels of significance. For both time periods, the GMM estimates of both the reduced-form regression coefficients and the structural parameters are qualitatively similar to those in Table 3. We again reject the parameter constraints imposed by the simple market-potential function. Compared to Table 3, GMM estimates of σ and μ tend to be smaller and of τ tend to be larger. Adding controls for exogenous amenities and human capital, as shown in columns (5) and (6), reduces the precision of the parameter estimates somewhat.

To see what the parameters imply about demand linkages between regions, I use parameter estimates from Tables 3 and 4 to calculate the effect of a shock that increases the augmented market-potential index by 10%. Since the shock is again defined as a percentage change in the market-potential index (though now it the augmented form), I can again use equation (16) to describe how the effect of this shock on wages varies with distance from its source.

Figure 3b plots equation (16) using coefficient estimates from columns (1) and (2) of Table 3. The results for the two time periods are similar. Changes in the market-potential index affect wages only if they occur within 200 km. These effects are substantially smaller than those based on the simple market-potential function in Figure 3a. Figure 3c plots equation (16) using GMM coefficient estimates from columns (1) and (2) of Table 4. Results for the two time periods are again similar, though in the later period the effects of the shock fall off more quickly with distance. Comparing Figures 3c and 3b, demand linkages between regions are much larger for the GMM estimates than for the nonlinear least squares estimates. In nonlinear least squares, the effects of measurement error may be leading to downward bias in the estimates of demand linkages between regions. Comparing Figures 3c and 3a, demand linkages between regions are smaller for the augmented market-potential function than for the simple market-potential function. While the two figures show similar effects of a nearby shock, in Figure 3c these effects fall off quickly with distance and are effectively zero once the location of the shock is beyond 400 km.

In unreported results, I performed additional checks on the sensitivity of the regression results. These include dropping high-population counties from the sample, dropping distant county aggregates from the summation expressions in (15'), estimating the augmented market-potential function for each region separately, using a more flexible distance function (as described in IV.A), and aggregating counties in the regressor function by state rather than by concentric distance bands. Results for these regressions are similar to those reported in Tables 3 and 4.

I also have estimated an augmented market-potential function based on a strict version of Krugman (1991), in which each region has an immobile agricultural labor force but no housing sector. This specification produces estimates of σ and τ that are qualitatively similar to those in Tables 3 and 4, but estimates of μ that are implausibly large. In all regressions, the data reject the strict of the Krugman model in favor of Helpman's (1998) extension of this model.

V. Discussion

In this paper, I use data on U.S. counties to estimate nonlinear models of spatial economic relationships. Recent theoretical work attributes the geographic concentration of economic activity to product-market linkages between regions that result from scale economies and transport costs.

My findings are broadly consistent with this hypothesis.

One contribution of the paper is the estimation of a simple market-potential function based on Harris (1954). I find that regional variation in wages is associated with proximity to large markets. While estimated demand linkages between regions are strong, they are limited in geographic scope. A second contribution of the paper is estimation of an augmented market-potential function based on Krugman's (1991) model of economic geography. This model has been very influential in theoretical research, and has begun to receive greater attention in empirical work. Estimates of the model's parameters are broadly consistent with theory. The data reject the simple market-potential function in favor of the augmented market-potential.

My findings, of course, do not rule out the possibility that other factors also contribute to spatial agglomeration. I show that the estimation results are not qualitatively affected by introducing controls for human capital externalities or exogenous amenities or by instrumenting for the augmented market-potential function. But there are other factors, such as technology spillovers, for which I do not control and which could have important effects on industry location.

Several aspects of the empirical results raise questions about the usefulness of the Krugman model for characterizing economic geography. Most importantly, estimated trade costs are large in value and rise in magnitude over time. In Figures 3a-3c, the magnitude of these costs implies that demand linkages between regions are very weak for regions separated by more than 1000 km. Sizable trade between distant regions suggests that actual trade costs may in fact be much lower. Also, available evidence suggests that communication costs and some types of transportation costs have been falling steadily over time (Cairncross, 1997). However, in defense of the results, the estimated increase in trade costs could reflect the ongoing secular shift in economic activity from low-trade-cost manufacturing to high-trade-cost services.

Some of the concerns about the empirical results could conceivably be remedied through generalizing the Krugman model, such as by introducing more heterogeneity in industry production and trade costs or by allowing for other motivations for spatial agglomeration. Recent work in trade theory (e.g. Eaton and Kortum 2002) allows for substantial industry heterogeneity. That the model has some explanatory power, despite its simplicity, is perhaps testimony to the importance of product-market linkages for the spatial distribution of economic activity.

The results of this paper relate to other work on the spatial demand linkages posited by new economic geography models. Redding and Venables (2004) evaluate such demand linkages, which they term market access, by estimating the cross-country correlation between per capita income and proximity to import demand, where the latter is constructed from estimated parameters of a gravity model of trade. They find that market access is positively correlated with per capita income, which corresponds to my finding that county wage growth is positively correlated with growth in a county's market-potential index. Thus, demand linkages appear to be strongly associated with wages whether one looks across countries or across regions inside countries.

While my approach is complementary to Redding-Venables, each has distinct advantages. An advantage of Redding-Venables is that by starting with a gravity model they are able to account for the importance of proximity to both import demand and export supply, thus permitting both consumers and firms to be sources of industrial demand. Advantages of my approach are that I am able to characterize the spatial distribution of economy activity at a highly disaggregated level and to uncover the model's structural parameters. If sufficiently disaggregated data on intraregional trade within countries were available, it should be possible to combine these two approaches.

Appendix: Estimation Results for Wage Controls

This table reports coefficient estimates on additional wage controls included in the regressions reported in column (7) of Table 2 and column (5) of Table 3. These same wage controls are also included in columns (8)-(9) of Table 2, column (6) of Table 3, and columns (5)-(6) of Table 4. I do not report results on the wage controls for these additional regressions, but they are very similar to those shown below. In each regression, the wage controls enter linearly. The wage controls include four sets of regressors: the 1980-1990 change in the share of the county population 16-64 years old by age category (20-24, 25-34, 35-44, 45-54, and 55-64); the 1980-1990 change in the share of the county population 25 years and older by years of schooling attained (9-11, 12, 13-15, 16 plus); average climate measures for the airport that is nearest to the county (average percent possible sunshine, average wind speed, average annual heating degree days, average annual cooling degree days, average humidity, average annual precipitation, and inland water area); and dummy variables for whether the county borders the sea coast or borders a one of the Great Lakes. County demographic data are from the *U.S. Census of Population and Housing* (taken from the *USA Counties 1996 CD ROM*) and climate measures are taken from the *Statistical Abstract of the United States, 1996* (Washington, DC: U.S. Department of Commerce, 1996).

	Table 2, Column (7)		Table 3, Column (5)	
	Coefficient	St. Error	Coefficient	St. Error
Change in Share of Population				
Aged 20-24	0.260	(0.140)	0.237	(0.138)
Aged 25-34	0.430	(0.072)	0.440	(0.072)
Aged 35-44	-0.480	(0.396)	-1.071	(0.387)
Aged 45-54	-0.057	(0.420)	0.469	(0.410)
Aged 55-64	-0.423	(0.121)	-0.347	(0.116)
Male	0.191	(0.213)	0.128	(0.212)
9-11 Years of Schooling	-0.086	(0.077)	0.046	(0.078)
12 Years of Schooling	0.032	(0.053)	0.099	(0.052)
13-15 Years of Schooling	0.153	(0.083)	0.045	(0.083)
16+ Years of Schooling	0.487	(0.121)	0.412	(0.119)
Log % Possible Sunshine	0.198	(0.024)	0.198	(0.026)
Log Average Wind Speed	-0.032	(0.003)	-0.006	(0.004)
Log Heating Degree Days	0.009	(0.006)	0.029	(0.008)
Log Cooling Degree Days	-0.041	(0.006)	-0.015	(0.006)
Log Average Humidity	0.002	(0.019)	0.055	(0.018)
Log Average Precipitation	0.073	(0.009)	0.049	(0.010)
Log Inland Water Area	-0.004	(0.009)	-0.003	(0.001)
Equals One if County				
Borders Coast	-0.002	(0.008)	-0.020	(0.007)
Borders Great Lake	-0.017	(0.007)	-0.008	(0.007)

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Table 1: Variable Means for U.S. Counties

(Standard Errors)

	Wage	Employment	Employ. Density	Personal Income	Housing Stock
1970	17.42	25,509	39.50	897,454	28,650
	(3.82)	(109,896)	(682.5)	(3,785,338)	(98,307)
1980	17.66	31,610	41.59	1,156,639	27,717
	(3.74)	(124,967)	(608.4)	(4,409,183)	(90,900)
1990	17.29	38,041	47.03	1,501,171	27,467
	(3.70)	(146,679)	(649.4)	(5,720,714)	(87,394)

Variable Definitions:

Wage	Average annual labor earnings (thousand of 1990 dollars) for wage and salary workers (Regional Economic Information System (REIS), U.S.BEA).
Employment	Average annual employment of wage and salary workers (REIS).
Employment Density	Employment per square kilometer.
Personal Income	Total personal income (thousands of 1990 dollars) (REIS).
Housing Stock	Total housing units (U.S. Census of Population and Housing).
Distance	Distance from a county to the mid point of a concentric distance band (not reported in the table above).

The Sample is 3,075 counties in the continental United States. County definitions are those for 1980. Each independent city in Virginia is combined with the surrounding county.

Table 2: Estimation of the Simple Market-Potential Function

Time Period	1970-80 (1)	1980-90 (2)	1970-80 (3)	1980-90 (4)	1970-80 (5)	1980-90 (6)	1980-90 (7)	1980-90 (8)	1980-90 (9)
(α_1) Market Potential	0.283	0.432	0.283	0.414	0.280	0.432	0.254	0.239	0.254
	(0.017)	(0.017)	(0.016)	(0.019)	(0.015)	(0.017)	(0.021)	(0.022)	(0.021)
(α_2) Distance	-5.465	-13.809	-5.465	-13.796	-5.534	-13.807	-15.352	-16.359	-15.352
	(0.746)	(0.964)	(0.718)	(1.067)	(0.721)	(0.934)	(1.796)	(2.118)	(1.796)
Adj. R^2	0.117	0.236	0.117	0.208	0.117	0.236	0.362	0.320	0.362
Log Likelihood	-16939.8	-16747.2	-16393.8	-14760.1	-16940.0	-16747.2	-16474.7	-14556.6	-16474.7
Schwarz Criterion	-16951.8	-16759.1	-16951.8	-14771.9	-16952.0	-16759.2	-16566.4	-14646.8	-16566.4
Counties	All	All	Low Pop.	Low Pop.	All	All	All	Low Pop.	All
Distance Bands	All	All	All	All	<1000 km	<1000 km	All	All	<1000 km
Wage Controls	No	No	No	No	No	No	Yes	Yes	Yes

The full sample is 3,075 counties in the continental United States; the low-population sample is counties in the continental United States with less than 0.05% of the U.S. population. The dependent variable is the log change in average annual earnings for wage and salary workers. The estimating equation for the simple market-potential function is equation (15), with α_3 constrained to be one and α_4 and α_5 constrained to be zero. Columns (5) and (6) exclude from the market-potential function county aggregates beyond 1000 km. from the county on which an observation is taken. Columns (7)-(9) add controls for county average education levels, demographic characteristics, climate and other factors. See the Appendix for the coefficient estimates on these variables (for column 7) and for more details on the wage controls. Heteroskedasticity-consistent standard errors are in parentheses. Parameters are estimated by nonlinear least squares. The Schwarz Criterion is ln(L)-k*ln(N)/2, where L is the value of likelihood function, N is the number of observations, and k is the number of regression parameters. Coefficient estimates for the constant term are not shown. See Table 1 for variable definitions.

Table 3: Estimation of the Augmented Market-Potential Function (Krugman Model)

Time Period	1970-80 (1)	1980-90 (2)	1970-80 (3)	1980-90 (4)	1980-90 (5)	1980-90 (6)
Market Potential	0.132	0.152	0.132	0.147	0.203	0.203
	(0.022)	(0.020)	(0.258)	(0.021)	(0.056)	(0.056)
Distance	-12.993	-17.907	-11.580	-17.561	-6.430	-6.429
	(1.071)	(0.906)	(1.006)	(0.953)	(0.520)	(0.520)
Personal Income	0.394	0.802	0.381	0.805	0.931	0.931
	(0.076)	(0.068)	(0.095)	(0.084)	(0.128)	(0.128)
Wages	7.202	5.760	6.997	5.974	4.004	4.006
	(1.271)	(0.823)	(1.439)	(0.953)	(1.313)	(1.314)
Housing Stock	0.606	0.198	0.619	0.196	0.069	0.068
	(0.076)	(0.068)	(0.095)	(0.084)	(0.128)	(0.128)
<u>Implied Values</u>						
σ	7.597	6.562	7.377	6.779	4.935	4.937
	(1.250)	(0.838)	(1.402)	(0.973)	(1.372)	(1.372)
τ	1.970	3.219	1.816	3.039	1.634	1.633
	(0.328)	(0.416)	(0.351)	(0.440)	(0.523)	(0.523)
μ	0.916	0.956	0.911	0.967	0.982	0.983
	(0.015)	(0.013)	(0.018)	(0.016)	(0.035)	(0.035)
$\sigma/(\sigma-1)$	1.152	1.180	1.157	1.173	1.254	1.254
	(0.029)	(0.030)	(0.034)	(0.029)	(0.089)	(0.089)
$\sigma(1-\mu)$	0.639	0.226	0.653	0.221	0.085	0.084
	(0.072)	(0.075)	(0.089)	(0.094)	(0.158)	(0.158)
Adj. R^2	0.256	0.347	0.217	0.296	0.376	0.376
Log Likelihood	-16698.1	-16576.9	-14699.4	-14662.2	-16479.9	-14573.0
Schwarz Criterion	-16714.0	-16592.9	-14715.0	-14677.9	-16575.5	-14667.1
Wald Test (p value)	0.000	0.000	0.000	0.000	0.001	0.001
Counties	All	All	Low Pop.	Low Pop.	All	Low Pop.
Wage Controls	No	No	No	No	Yes	Yes

The estimating equation for the augmented market-potential function is (15'). Heteroskedasticity-consistent standard errors are in parentheses. Parameters are estimated by nonlinear least squares. The Wald test statistic (p value) is for the hypothesis that α_3=1, α_4=0, and α_5=0. Columns (5) and (6) include additional wage controls in the estimation (see notes to Table 2). The Appendix shows coefficient estimates on these controls for the regression in column (5). The reported structural parameters are:

σ = the elasticity of substitution between any pair of traded goods.
μ = the share of expenditure on traded goods.
τ = transportation costs (for units of 1000 km.).
$\sigma/(\sigma-1)$ = ratio of price to marginal cost.
$\sigma(1-\mu)$ = stability condition for the spatial distribution of economic activity.

Table 4: GMM Estimation Results for the Augmented Market-Potential Function

Time Period	1970-80 (1)	1980-90 (2)	1970-80 (3)	1980-90 (4)	1980-90 (5)	1980-90 (6)
(α_1) Market Potential	0.487	0.393	0.492	0.488	0.467	0.573
	(0.119)	(0.164)	(0.119)	(0.207)	(0.372)	(0.271)
(α_2) Distance	-11.163	-15.400	-11.145	-16.597	-16.175	-15.108
	(2.081)	(2.054)	(2.082)	(3.312)	(3.453)	(2.366)
(α_3) Personal Income	0.120	0.664	0.121	0.615	0.834	0.754
	(0.046)	(0.138)	(0.046)	(0.127)	(0.338)	(0.169)
(α_4) Wages	1.934	1.882	1.908	1.435	1.306	0.992
	(0.519)	(0.957)	(0.509)	(0.770)	(1.398)	(0.703)
(α_5) Housing Stock	0.880	0.336	0.879	0.385	0.166	0.246
	(0.046)	(0.138)	(0.046)	(0.127)	(0.338)	(0.169)
Implied Values						
σ	2.053	2.546	2.028	2.050	2.140	1.745
	(0.500)	(1.064)	(0.490)	(0.869)	(1.705)	(0.827)
τ	10.593	9.964	10.836	15.800	14.188	20.272
	(5.585)	(7.129)	(5.737)	(14.901)	(18.875)	(20.626)
μ	0.545	0.821	0.539	0.732	0.873	0.752
	(0.113)	(0.154)	(0.114)	0.218	(0.385)	(0.317)
$\sigma/(\sigma-1)$	1.934	1.647	1.972	1.950	1.877	2.341
	(0.519)	(0.446)	(0.463)	(0.787)	(1.312)	(1.488)
$\sigma(1-\mu)$	0.935	0.456	0.935	0.550	0.272	0.433
	(0.025)	(0.210)	(0.025)	(0.221)	(0.614)	(0.359)
Adj. R^2	0.160	0.314	0.159	0.298	0.327	0.309
Wald Test (p value)	0.000	0.000	0.000	0.000	0.015	0.002
Chi-Square (p value)	0.343	0.200	0.254	0.167	0.206	0.327
Instrument Set	Narrow	Narrow	Broad	Broad	Narrow	Broad
Wages Controls	No	No	No	No	Yes	Yes

Parameters are estimated by GMM. The narrow set of instruments is 10, 20, 30, and 40 year lagged values of country population growth in the own county and in immediately surrounding counties; the broad set of instruments adds to this set similar lagged values of more-distant-county population growth. The Chi-Square test statistic (p value) is for a test of overidentifying restrictions on the instruments. Heteroskedasticity-consistent standard errors are in parentheses. Columns (5) and (6) include additional wage controls in the estimation (see notes to Table 2 and Appendix). See notes to Table 3 for additional details on the estimation.

Figure 1: Log Change in Employment Relative to U.S., 1970-1990

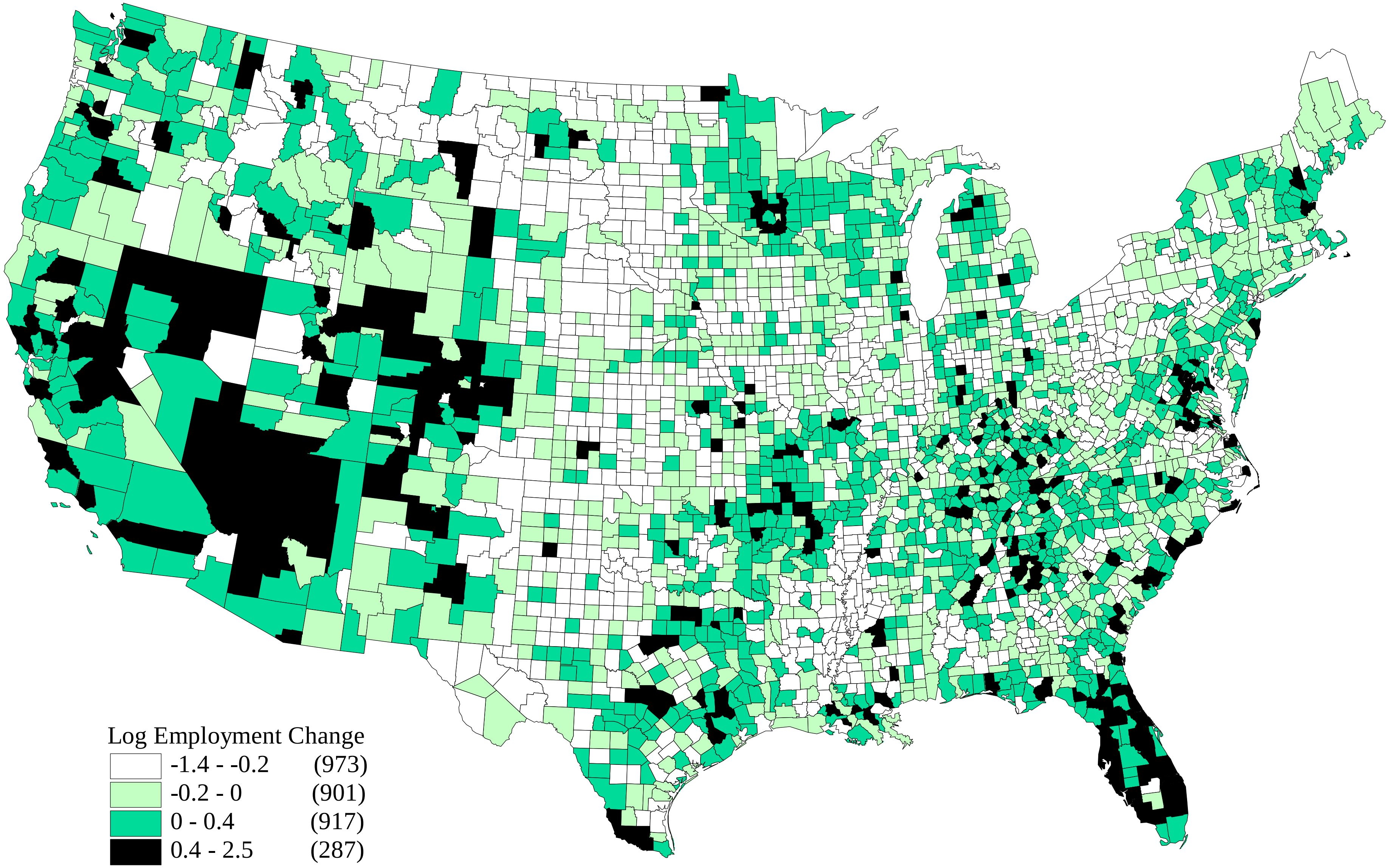


Figure 2: Log Change in Average Wage Relative to U.S., 1970-1990

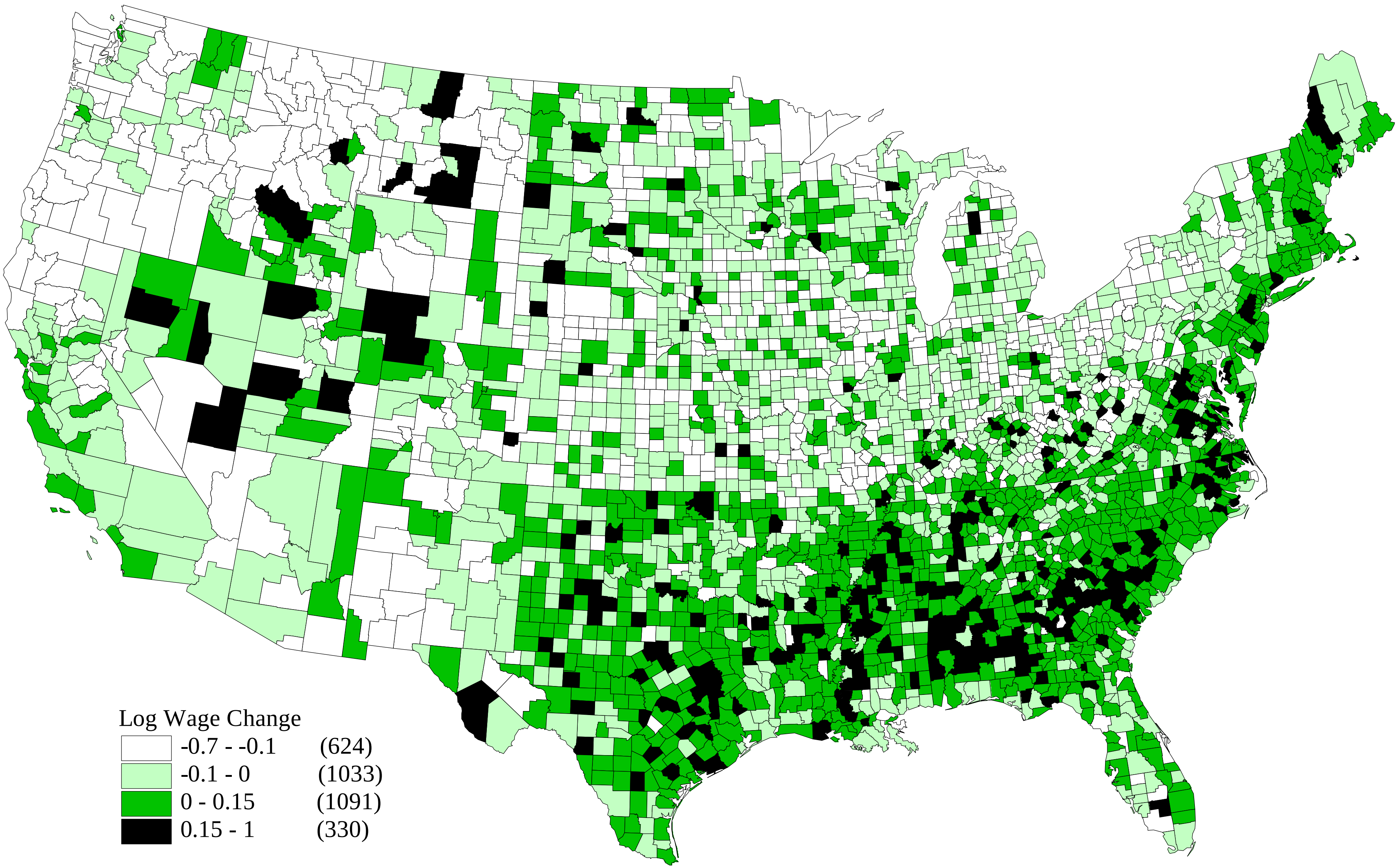
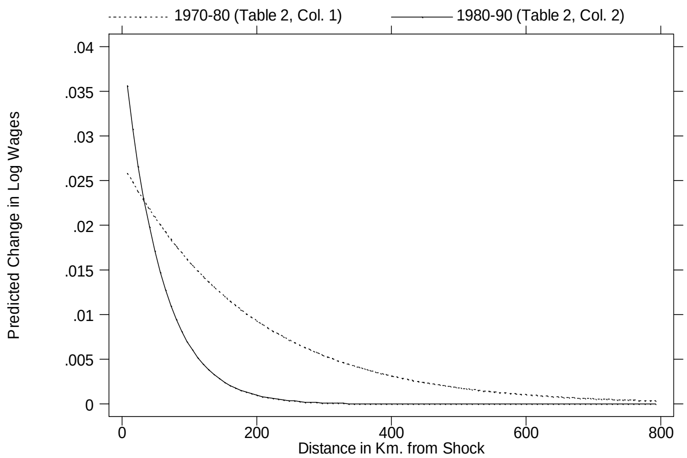
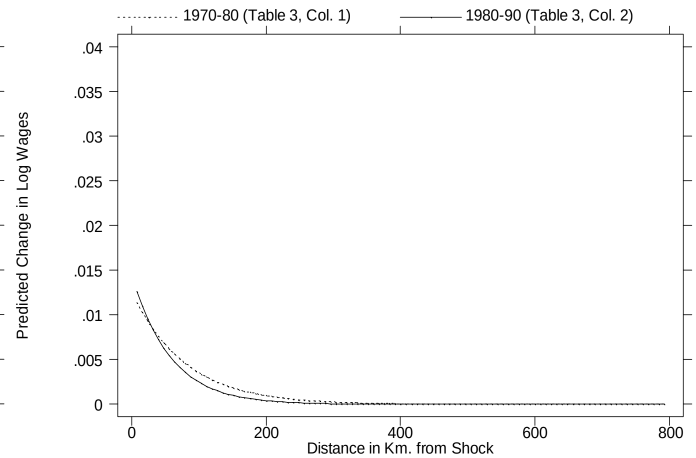


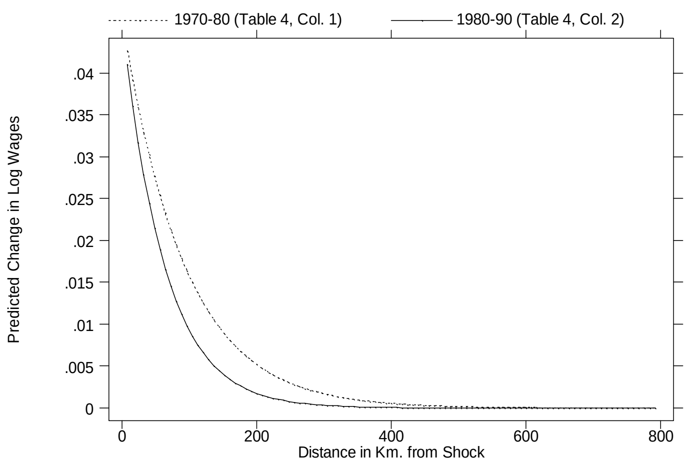
Figure 3: Spatial Decay of Predicted Wage Changes

(a) Simple Market Potential Function (Nonlinear Least Squares, Table 2)



(b) Augmented Market Potential Function (Nonlinear Least Squares, Table 3)





(c) Augmented Market Potential Function (GMM, Table 4)