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# Resilience from the micro perspective

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**Abstract**

Perhaps uniquely, we combine individual-level data from the American Community Survey 2005-2011 with aggregate data for small areas to examine the resilience of individuals' wages to the 2008 economic crisis. A Mincer-type wage equation, incorporating market potential and employment density is estimated, leading to a measure of resilience based on actual wages in 2011 and on a counterfactual obtained from our wage equation. We find that individuals living in areas with a higher level of market potential are more resilient, controlling for individual-level characteristics such as education and ethnicity, indicating that both individual-specific and place-specific factors are important.

**Key Words: Resilience; Urban Economics; New Economic Geography; Counterfactual; United States**

**JEL Codes: P48; J31**

## Introduction

There has been considerable attention paid to the impact of shocks on both regional and national economies, with a number of alternative approaches adopted. These include case studies, the generation of indices, time series analysis and causal economic models, with the focus being on national, regional or city economies (Ormerod 2010, Foster 2007, Fingleton, Garretsen and Martin 2012, Doran and Fingleton 2014, 2013). The typology of resilience studies is discussed in detail in Martin and Sunley (2013), however, to date there has been little if any work on resilience which uses the individual as the unit of analysis. This microlevel analysis is the main contribution of the paper, since to our knowledge all previous geographically-oriented empirical work on resilience has been at an aggregate level and thus does not consider potentially resilience inducing individual-level factors. We focus on the impact of the 2008 economic crisis on individual wages in the US.

The study is motivated by the recent interest in the concept of resilience, and specifically the resilience of wages, to shocks at the level of regions or cities (Fingleton and Palombi 2013) as well as by the recent application of regional wage models to micro-data series (Fingleton and Longhi 2013, Hering and Poncet 2010). This paper combines these two strands of the literature on wages (resilience and regional wage models) to analyse the resilience of individual level wages to economic shocks.

The starting point of the paper is a model of wages at the individual level, while also incorporating determinants of wages measured at the aggregate (areal) level, over the period 2005 to 2007. Specifically, we estimate a model of individual wages, incorporating individual specific characteristics [ *à la* Mincer (1974)] and areal factors [market potential and employment density which, under New Economic Geography (NEG) and Urban Economic (UE) theory respectively, should also determine wage levels]. We estimate this model using data from the American Community Survey 2005 to 2007 which is an annual survey conducted by the US Census Bureau and is the largest individual survey the US Census Bureau conducts with the exception of the census. These individual level data are combined with the Public Use Microdata Area (PUMA) data, which are at the lowest level of spatial disaggregation available[i]. We use the acronym PUMA throughout the paper to refer to data at this level of spatial aggregation. The focus on the individual level helps allay possible self-selection problems associated with aggregate regional level analysis, such that high wages, which typically occur in cities, may simply be attributable to highly productive and qualified mobile individuals choosing to work in cities, rather than any inherent benefits imparted by a city location per se. Thus, working at the individual level we should be able to moderate the wage-premium commonly associated with city locations, by controlling for individual level variables that also have an impact on wages, thus taking account of self-selection.

Having estimated our wage equation, we then combine the estimated model parameters with projected values of the variables driving wage levels through the (early) period of the recession, with projected values obtained on the basis of assumptions about the trajectory of the drivers under a no-recession counterfactual. Given wage levels thus obtained under the counterfactual, the paper explores how the recession has affected individual wage levels differently, according to gender, education, social and economic status and age, and seeks to determine which, if any, individual characteristics convey resilience. Given the individual level effects, the paper also examines the significance of market potential and employment density.

The structure of the paper is as follows. Section 2 provides a brief review of the related resilience literature, putting the current paper in context. Section 3 outlines the theoretical background to our analysis including Mincer's (1974) wage equation, which is specific to the individual, and our PUMA-level indicators; market potential derived from NEG theory and employment density derived from UE theory. The empirical approach employed, together with how we obtain our counterfactual estimates for resilience, are outlined in Section 4. Section 5 describes the data used in the paper. Section 6 gives model estimates, Section 7 describes geographical patterns of resilience, Section 8 discusses resilience at the individual level and Section 9 concludes.

**Resilience to Shocks**

The responses of national and regional economies to economic shocks has long been a focus of analysis with increased interest in the topic of resilience following the 2008 economic crisis (Martin 2012, Friedman 1964, Romer 2001, Fingleton et al. 2012). The focus of the recent resilience literature has been on the impact of shocks, be they economic or some other form, on the growth path of regions and nations (Simmie and Martin 2010). Indeed the central question is often whether temporary shocks result in a permanent or temporary effect[ii] on either GDP or employment within a region (Cross, Grinfeld and Lamba 2009, Grinfeld, Cross and Lamba 2009).

Analysis of the effects of economic shocks has been enhanced by consideration of the observed growth path of the economy through recession in relation to what would have otherwise happened, and various modelling strategies have been adopted in order to create the necessary counterfactual series. Doran and Fingleton (2014) obtain counterfactual productivity predictions for EU countries on the basis of vector error correction models. Fingleton, Garretsen and Martin (2014) develop counterfactuals for employment levels and growth across EU regions based on spatial panel models. Similarly, Fingleton and Palombi (2013) use spatial panel models to measure resilience in the context of counterfactual wage series, in their case wages paid in British cities in the Victorian era. They note that shocks appear to have a permanent effect on wage levels, but that industrial structure and other factors may convey resilience to city economies. In this paper we also focus on the resilience of wages, but rather than using city or regional averages we are fortunate in having wage data and covariates at the individual level.

## The Determinants of Individual Wages

Our empirical analysis of the impact of the 2008 economic shock is based on a model of the determinants of individual wages which naturally divide into two groups, firstly individual specific factors and secondly PUMA-level factors. In order to identify individual specific factors we appeal to Mincer's (1974) wage equation, which has a long established literature describing the positive impact of human capital on wages (Heckman, Lochner and Todd 2003). At the regional (PUMA) level, we appeal to New Economic Geography (NEG) and Urban Economics (UE) theory, which suggest that regions or cities with high levels of market potential or employment density will tend to have higher levels of wages. We refer the interested reader to Ciccone and Hall (1996) and Fujita et al. (1999) for derivations of the respective models.

### *Mincer's Wage Equation*

As noted by Lemieux (2006) the most widely used form of the seminal Mincer (1958, 1974) wage equation relates log earnings to years of education and experience[iii]. More precisely, the model captures the impact of human capital investment on income returns, with schooling an equilibrium outcome as a result of investing in education in order to maximise the present value of income. The experience element of the model captures the subsequent development of human capital post-schooling. This type of specification has become so well established that it has been referred to as a "cornerstone of empirical economics" (Heckman et al. (2003: pg. 1). However, as noted in Lemieux (2006), it has now become standard to not just include schooling and experience in the wage equation, but also a variety of other individual specific factors which may impact on wages (Fingleton and Longhi 2013).

In addition to individual factors our approach is to build an empirical model that captures two important regional-level influences on wages. This is consistent with Fingleton and Longhi (2013) and Hering and Poncet (2010). One is market potential, which provides an indication of a region's centrality with respect to supply of and demand for the region's goods and services. The benefits of locating where there is good market access means that firms are able to offer higher nominal wages to workers in certain locations, thus providing part of the explanation of why wage levels vary spatially. The rationale for this is NEG theory, although we do not explicitly summarise this as it is widely available in the standard literature (Fujita et al, 1999). The basic relationship coming from this theory, which is one of a set of simultaneous equations associated with the short-run equilibrium prior to labour mobility with respect to real wage differentials, is

$$\ln w_i = \frac{1}{\sigma} \ln P_i \qquad (1)$$

Where $w_i$ is nominal wage at location $i$, $P_i$ denotes market potential at $i$, and $\sigma$ is a scalar parameter. We use the reciprocal because of the theoretical provenance of equation (1).

However, NEG theory on its own has had only limited success in explaining the granularity of localised wage differences (Fingleton 2011), and we therefore enhance our model to try to pick up specific city-oriented rather than region-oriented effects. For this component of our model we appeal to Urban Economics theory, but again we do not set this out explicitly, instead we simply make use of the main result coming from this branch of economics that wages are a function of employment density. In other words there are specific advantages accruing to dense cities because of the complex variety of services available locally in cities that enhance productivity proportional to city density, leading to a reduced form involving employment density, with consequences for wage levels. The detailed theoretical and empirical rationale for this relationship between wages and density can be found in the literature, most notably Ciccone and Hall (1996), Abdel-Rahman and Fujita (1990), and Rivera-Batiz (1988). For our purposes we simply make use of the reduced form in loglinear terms, which is

$$\ln(w) = \gamma + \phi \ln(E) \tag{2}$$

In which $E$ denotes employment per square mile (or km) and $\gamma$ and $\phi$ are scalar parameters.

## Empirical Approach

### *Model Specification and Estimation Approach*

Our approach combines the two separate explanations of wage variation (coming from NEG and UE theory) as a single, hybrid model (Fingleton, 2006). We could opt to reduce the model to one or other theory-consistent specification if inferential rules allow but, as we show below, in our case both theories carry significant information with regard to the determinants of wage levels.

Therefore the econometric model is specified based on a Mincer's style wage equation incorporating variables at the individual level augmented by our PUMA-level indicators of market potential and employment density. The Mincerian element of our econometric specification relates individual wages to individual specific characteristics such as education, gender and sector of employment. The regional variables capture the impact of the individual's location on his or her level of wages. The model combining individual and areal effects is given in equation (3),

$$\ln w_{it} = \alpha + X_{it}\beta + \frac{1}{\sigma}\ln P_{rt} + \varphi \ln E_{rt} + \mu_r + \mu_t + \mu_{it} \tag{3}$$

In which $\ln w_{it}$ is the log of wages of individual *i* in time period *t*, $\alpha$ is a constant term, $X_{it}$ is a matrix of variables representing the characteristics of individual *i* including age, age$^2$, education, marital status and gender, among others and $\beta$ is the associated vector of coefficients. $\ln P_{rt}$ and $\ln E_{rt}$ are vectors containing measures of market potential and employment density for PUMA *r* in time period *t* and $\sigma$ and $\phi$ are the associated coefficients. Additionally we include sets of dummy variables capturing unobserved variation across PUMAs and across time. Thus $\mu_r$ is a vector of PUMA fixed effects where *r*=1…*K* PUMAs[iv] and $\mu_t$ is a matrix of year fixed effects where *t*=2005 to 2007. Also $\mu_{it}$ is the individual specific error term for person *i* in time period *t*. This approach is similar to that of Dalmazzo and de Blasio (2007b, 2007a), Di Addario and Patacchini (2008) and Bratti and Leombruni (2009). Note that, consistent with this literature, as we do not have true panel data we do not have individual level fixed effects. This could lead to sorting effects across areas, for example, omitting individual 'earning ability', where able individuals sort (or choose to locate) into denser central cities (on the basis of some other correlated city characteristics, such as amenity).

This would not be an issue if we were sure we had data on *all* the individual characteristics that affected wages.

While our Mincerian approach provides a good basis for assuming that we have captured the main causes of inter-individual wage variation, we cannot be entirely certain that this is the case. In our example high market potential and dense central city locations may also be high 'ability' locations, where 'ability' is an omitted variable[v] and so, as shown below, we treat this as an endogeneity problem. In addition, the inclusion of PUMA level fixed effects should also capture the impact of omitted variables at the PUMA level which could drive heterogeneity in individual wages.

As noted by Canton (2009) it is likely that $\mu_{it}$ is correlated within areas as area-specific elements may be impacting on all the people within that area. Therefore, to allow for intra-PUMA correlation we cluster our errors according to PUMA which generates appropriate standard errors[vi].

The set of variables included in the matrix $X_{it}$ are gender, marital status, industry and hours worked, plus traditional Mincer-type variables such as level of schooling and age (which proxies for experience) (Heckman et al. 2003, Lemieux 2006). The full suite of variables is listed in Table 1.

As described above, endogeneity bias could occur if there are omitted variable(s) causing the error term to be correlated with our explanatory variables. Typically this may be an outcome of sorting into high amenity or network-rich, urban locations[vii] (Venables 2011). In an attempt to control for endogeneity, we utilize various instrumental variables defined as follows. First we apply Bartlett's three group method (initially introduced in the context of endogeneity caused by measurement error) in order to create instruments correlated with market potential and employment density and yet (possibly) independent of the errors. Bartlett's (1949) three group method simply divides the endogenous variable into three categories based on the size of the variable. The n/3 smallest are set to -1, the n/3 largest are set to 1 and the n/3 middle values are set to zero (Johnson 1984, Kennedy 2008). The process was initially designed to address measurement error but can be applied in the context of endogenous regressors (Fingleton 2003, Artis, Miguelez and Moreno 2012, Le Gallo and Páez 2013). On a note of caution, Fingleton and Le Gallo (2007) show that three-group instruments are typically pseudo-instruments rather than true instruments, in that if they are based on an endogenous variable an element of correlation with the errors will be retained, and so while they will tend to reduce endogeneity-induced bias, they may not eliminate it totally.

Therefore, we also include an additional set of instruments based on the synthetic instruments approach developed in Le Gallo and Paez (2013). They outline a five step procedure which produces a synthetic instrument for each endogenous variable. We briefly outline their approach here but refer interested readers to the full explanation in Le Gallo and Paez (2013). It starts by defining a contiguity matrix, in our case a matrix of inter-PUMA contiguity, and obtaining the eigenvectors of this matrix. Then each eignvector is regressed on the endogenous variable and the significant eigenvectors are retained and summed to create an exogenous instrument (each significant eignvector is weighted according to the regression coefficient obtained by regressing the eignvector on the endogenous variable) [viii]. We generate a third set of instruments by following the general approach proposed in Le Gallo and Paez (2013), however, in this instance we do not differentially weight the significant eignvectors by their respective coefficients, but simply sum the positively related ones. This unweighted version provides an alternative which is also orthogonal to the disturbances[ix]. Regardless of whether we use the original Le Gallo and Paez (2013) method or our alterative unweighted approach the results are similar. When we apply the approaches based on Le Gallo and Paez (2013) we generate the instruments for each year separately and then stack these to give us our instruments for 2005 to 2007.

*Generating Counterfactual Wage Series*

Given consistent estimates of the model coefficients as a result of the application of instrumental variables, counterfactual values for wages of individual *i* are generated using the following equation:

$$\ln \hat{w}_{i2011} = \hat{\alpha} + X_{i2011}\hat{\beta} + \frac{1}{\hat{\sigma}} \ln P_{r2011} + \hat{\varphi} \ln E_{r2011} + \hat{\mu}_r + \hat{\mu}_{2007} \quad (4)$$

In (4), $\hat{\bullet}$ denotes consistent estimates resulting from fitting equation (3) for data covering the period 2005-2007. As is evident in (4), we predict wage levels for the year 2011 using the assumed 2011 values for the individual variables denoted by $X_{it}$ and projected 2011 values for log market potential ($\ln P_{rt}$) and log employment density ($\ln E_{rt}$). We also use the estimated PUMA level dummy coefficients to control for PUMA specific effects. Additionally, using the year 2007 dummy to control for the time trend, we eliminate inflation over the period 2007-11.

Given counterfactual wages, we are now in a position to assess the resilience of individuals to the crisis based on the difference between $\ln w_{i2011}$ (the actual 2011 wages) and $\ln \hat{w}_{i2011}$.[x] This then allows us to examine possible differences in resilience across areas or with respect to individuals' characteristics, such as gender, age and education, in order to see whether individual characteristics convey resilience.

*Generating Counterfactual Independent Variables*

In order to generate counterfactual forecasts for individual resilience we need to acquire counterfactual input series, *X*, *P* and *E*, for our model. Obtaining these input series is relatively straightforward for our individual level variables *X* as we simply utilise the 2011 indicators for education, gender etc. We do not expect these to have been affected by the economic crisis, in other words the observed individual variables are assumed to be the same as what one would observed under the no-crisis counterfactual. The main issue arises when considering our PUMA-level variables; market potential and employment density. Both of these have changed substantially over the crisis period. Therefore, we do need to generate a no-recession counterfactual for these two variables. We generate a no-recession counterfactual for employment density and market potential resulting from applying the average annual rate of growth of these variables from 2005 to 2007, compounded to 2011. This assumes that growth would have continued at pre-crisis levels had the 2008 economic crisis not occurred.

*Measures of Resilience*

In order to analyse the resilience of individuals we construct a measure of resilience, namely proportional resilience $(R_P)$. This is simply the difference between actual and counterfactual wages $(R_A)$ at the end of our period of analysis (2011) scaled by actual wages (in 2011), as shown by equation (5),

$$R_P = \frac{R_A}{\text{Actual Wages}_{2011}} \tag{5}$$

Proportional resilience thus scales absolute resilience $(R_A)$ such that a given wage difference will have a bigger proportional impact on the poor than on the rich. We prefer this approach because we believe that a higher income will by itself impart resilience to a shock and in controlling for the effect of wage level we are obtaining a more appropriate measure of resilience. Negative values indicates that an individual has wages below the counterfactual wage level and the more negative the value the less resilient an individual is to the shock.

The resilience indicator $(R_P)$ by individual then becomes the dependent variable in our model, and we endeavour to measure the impact of variables such as the age or educational attainment of individuals on this individual-level resilience measure. Additionally we obtain PUMA-level proportional resilience as the mean $R_P$ averaging across all individuals resident in a given PUMA. This gives us approximately 2,100 PUMA $R_P$ s which become the dependent variable in an ancillary PUMA-level model.

*Factors Determining Resilience*

Once we calculate our resilience indices we can use the proportional resilience measure, at the level of the individual (or at the area, PUMA, level), as a variable to be explained. At the individual level, our model is given by equation (6)

$$R_{Pit} = \alpha + X_{it}\beta + \frac{1}{\sigma}\ln P_{rt} + \varphi \ln E_{rt} + \mu_r + \mu_{it} \tag{6}$$

in which $R_{P_{it}}$ is the proportional resilience of person *i* in time period *t* where *t* is 2011 and matrix X contains individual-specific variables. This is similar to equation (3) except that rather than explaining wages we are here attempting to explain resilience. Again we do not have fixed individual effects and thus attempt to again counter endogeneity via the use of instrumental variables. We also control for PUMA fixed effects.

**Data**

In this paper we are interested in exploring the impact of the 2008 economic crisis on individual level wages in the US. We ask what would wages have looked like had the crisis not occurred and compare the observed wages in 2011 with counterfactual predictions obtained under a no-recession counterfactual. Essentially we are concerned with examining whether, by 2011, wages had been depressed by the crisis to a level below their counterfactual level or whether they had proven resilient (i.e. actual wages had rebounded to their counterfactual level or had not been impacted by the crisis). If they have been resilient, we ask what factors contributed to that resilience.

The data we use are derived from The Integrated Public Use Microdata Series (IPUMS-USA); specifically the data are from the American Community Surveys (hereafter ACS) of 2005-2011 which is an on-going statistical survey by the U.S. Census Bureau. The ACS is a repeated cross sectional survey, and therefore it is not a panel dataset but a pseudo-panel as it surveys different individuals in each wave. However, the questions are consistent across years allowing the data to be pooled in a manner similar to Dalmazzo and de Blasio (2007b, 2007a) and Canton (2009) who construct pseudo-panels for various repeated cross-sectional surveys. In our data set, the average wage across years varies between \$45,000 and \$48,000 while the average age of survey respondents is just over 45 years. The sample is predominantly male with a roughly 60/40 split, and the majority of individuals surveyed are married. The ethnic composition is mixed but the majority of people are white. Most have at least a Grade 12 education, while approximately 35% have at least 4 years college education.

The ACS microfiles also contain the Public Use Microdata Areas (PUMA) data. PUMAs (as in Figure 1) are non-overlapping regions which partition each state into areas each containing about 100,000 residents, and were first made available in ACS micro files in 2005[xi]. The presence of geographical identifiers in our dataset allows us to incorporate measures of market potential and employment density into our model specification. In total, given about 2,100 PUMAs in the US, we have about 2,100 measures of market potential and employment density alongside approximately 650,000 individual observations annually.

The information required for the generation of our market potential variables is obtained from 'The American Factfinder' and is derived from ACS estimates of employment at the PUMA level. Our starting point is equation (7),

$$P_i = \sum_{r=1}^{R} Y_r (G_r^M)^{\sigma-1} \overline{T}_{ir}^{\,1-\sigma} \tag{7}$$

in which $P_i$ denotes market potential in area *i*, and we sum across a set of *R* areas to obtain this. The variable $Y_r$ is the level of income in area *r*, $G_r^M$ is the price index for the *M* sector[xii] in area *r*, and $\overline{T}_{ir}$ is the transport cost between areas *i* and *r*. Also, following from established literature the elasticity of substitution $\sigma = 6.25$, an assumption based on the summary of empirical estimates presented in Head and Mayer (2003). This value is also used in Fingleton (2011). Note that this is the same $\sigma$ as in equations (1, 3 and 4) but in these equations it is an estimate based on empirical data. Note that strictly this equation relates to *M* sector wages, but we simplify by setting the price index equal to 1 across all areas, so that market potential then relates simply to income levels and transport costs, and this more informal specification can then be related to wages overall.

When defining trade costs in equation (8) we use the distance between PUMAs, thus $\overline{T}_{ir} = e^{\tau \ln D_{ir}}$ where $D_{ir}$ is the straight line distance between the main towns of area *i* and area *r* respectively and the $\tau$ parameter defines the rate at which trade costs increase with distance. Ideally, this would be estimated using trade data as in Redding and Venables (2004), however, at the PUMA level this is not possible as no statistics for trade are available. Therefore, following the published literature we assume a value for $\tau$ equal to 0.1 (Fingleton 2006). This assumption produces plausible levels of market potential which accord with our *a priori* notions, as described in Figure 1. Varying the assumed value of $\tau$ within a reasonable range does not distort the resulting geographical pattern too greatly, so we are reasonably confident that our market potential variable is a robust and reasonable measure.

The market potential map presented in Figure 1 shows the highest concentration (darker shading) is on the East coast of the US with two pockets of high market potential on the West coast, centred around major urban concentrations.[xiii] Low market potential prevails across the central and Western states, with obvious exceptions for large urban concentrations.

[insert Figure 1 around here]

In contrast to our NEG motivated market potential variable, the link to UE theory is simply via employment density, defined as employment per square kilometre. Figure 2 presents the 2007 employment density map again using the geographical framework of the PUMAs. Quite naturally employment density is also highest around the core urban areas of the US, as depicted on the map by the regions with darkest shading.

[insert Figure 2 around here]

**Model Estimates**

We consider first the determinants of wages then resilience. Table 1 gives the estimates of equation (3), relating individual level wages to individual and areal factors. This is the 'workhorse' equation which is the basis of our counterfactual wage levels. We present three estimates of equation (3), each using alternative instrumental variables. Model 1 refers to the use of Bartlett's three group method, Model 2 refers to the Le Gallo and Paez (2013) instruments and Model 3 refers to our alternative Le Gallo and Paez (2013) instruments which exclude the weighting of the eignvectors by their respective coefficient. We note that regardless of the instruments used our results appear robust and do not vary to any great extent.[xiv]

The table shows that both our areal variables are significant and positive, thus indicating that wages are higher in areas with higher employment density and market potential. This finding is consistent with the individual level analysis of Fingleton and Longhi (2013).

When we consider our individual level variables, we find evidence for a quadratic relationship between age and wages, with the positive coefficient on age and the negative coefficient on age-squared, indicating that wages increase with age up to a point, and then fall. We also find that females tend to have lower wage levels than males, and being married has a positive effect. When we consider ethnicity, 'White' (the default category) and 'Japanese' individuals earn the highest wages while 'Chinese' ethnicity is associated with the lowest wages. Also individuals who work more weeks during the year achieve higher wage levels. In line with much of the literature, we find that individuals with higher levels of education earn higher wages, and this is a systematic effect, as evidenced by an increase in the magnitude of the coefficient as education increases. In addition, sector of employment affects wages, with workers in the mining, utilities, and finance-related sectors earning high wages, while service sector occupations such as food services are associated with lower wage levels. These service activities are predominantly to be found in urban locations, so while workers in urban locations per se would seem to earn higher wages, some typical urban occupations are poorly paid.[xv]

[insert Table 1 around here]

**Geographical Patterns of Resilience**

To calculate the proportional resilience indicator, we apply the Table 1 estimates as in equation (4).[xvi] Focusing on the PUMA level of geographical aggregation (State-level analysis is rather uninformative with no obvious geographical pattern in evidence), there is substantial geographical heterogeneity but this is characterized by significant spatial autocorrelation. For the entire US, the Z value for the Moran's I statistic[xvii] for PUMA proportional resilience is 84.29 with an associated p-value of less than 0.0001. This suggests that resilient regions are likely to be located near to other resilient regions and less resilient regions are also likely to be spatially clustered. As an example of regional heterogeneity we can consider Figure 3, which presents typical maps[xviii] showing PUMA-level variation within States containing major city regions (in this case New York and California). Darker shading denotes more resilience, since it is associated with the least negative values. We can compare these and other city regions, which comprise small densely populated PUMAs, with more rural, less densely populated PUMAs. Looking closely at these and other similar maps for all the major city regions of the US it is evident that a significant number of small inner urban areas have proven relatively less resilient to the crisis, possessing lower levels of proportional resilience.

This apparently low inner urban area resilience is also evident when we regress aggregate (PUMA level) resilience on employment density, market potential and PUMA-level covariates equivalent to the individual-level covariates[xix]. The main feature of this ancillary regression is that market potential has a positive link to proportional resilience but employment density has a negative association.

[insert Figure 3 around here]

**Resilience at the Individual Level**

Analysis of resilience at the individual level is based on equation (6) with the resulting estimates given in Table 2. Again the use of Model 1 through to Model 3 refers to the instruments used in the estimation and their use matches that in Section 6. This shows that individual educational attainment is significantly related to resilience, with those with a college education being more resilient than those without. Clearly there is a bonus associated with striving to achieve more than one year of college education, since the extra effort and sacrifice involved is rewarded in terms a substantially higher resilience. Overall, highly educated respondents earned the highest wages and this itself would have contributed to a higher level of proportional resilience.

With regard to gender, our equation (6) estimates suggest that females are more resilient than males. In the case of age, we again assume that a quadratic relationship between age and resilience is a reasonable approximation, forming the inverted U-shaped relationship typical of many Mincerian wage models, with the youngest and oldest individuals being the least resilient and middle aged individuals being the most resilient.[xx] Table 2 also highlights differences according to ethnicity and sector of occupation, with mining standing out as being relatively resilient, and various services and retail jobs among the least. Table 2 also presents F-tests of our variables to assess joint significance.

Regarding our PUMA level variables, employment density has a negative effect on resilience while market potential has a positive effect. This suggests that even when controlling for individual specific characteristics as well as unobserved regional level variables using PUMA fixed effects, employment density and market potential still matter. They have independent effects and are not simply proxying for unknown omitted (time-invariant) variables. With regard to the significance of employment density, although the elasticity is comparatively very small, this suggests that the effect is not simply due to some unknown regional factor(s) or the presence in some inner city locations of vulnerable people, but there seems to be a real effect that is transmitted across groups. We speculate that an inner city high density location is a catalyst for externalities that make them places where resilience is lower than it otherwise would be. This does not mean of course that such central locations necessarily actually have lower resilience, because it is also the case that many such locations have a high level of market potential, and may also be affected by the unobserved variables captured by our PUMA dummies, and some of these could counteract the downward pull on resilience of the inner city. What we do observe is a small reduction of resilience effect in inner urban areas with high employment density, while those regions with better market access appear, *ceteris paribus*, relatively more resilient.

[insert Table 2 around here]

**Conclusions**

In this paper we analyse the resilience of individual level wages with respect to the 2008 economic crisis, using the American Community Survey 2005-2007 and 2011. We find that as a result of the 2008 economic crisis, wages fell relative to what one would anticipate under a no-crisis counterfactual, but the extent of the fall depends on individual characteristics, and it also appears to be related to where individuals lived, with those in inner city high density locations and in areas with better market access experiencing an effect due to their location, as suggested by Figure 3 and similar maps. These maps suggest that living in some areas with higher levels of employment density (typical urban concentrations) is a cause of lower resilience to the 2008 economic shock. This apparent causal effect persists in our micro-level analysis. Thus when we examine the outcome of estimating equation (6), as shown in Table 2 employment density remains negatively related to resilience. Therefore, in addition to the level of resilience attributable to the characteristics of the individuals, place effects persist in the form of significant effects as a result of unobserved factors captured by PUMA-level fixed effects, but these do not wipe out the significance of variations in market potential and employment density.

In contrast to the small negative employment density effect, we observe a large positive effect of market potential, leading us to conclude that living in a location with good market and supplier access imparts resilience in addition to the effects on resilience of having a college education, or being of a certain age, ethnicity or industrial sector. Although we base our analysis on a well established Mincerian wage equation and so hopefully capture the main determinants of wages and resilience in our models, we nevertheless take a cautionary approach, mindful of the possibility of sorting. In other words sorting due to omitted variables could still be an issue because we are not able to control for individual unobservables via fixed or indeed random effects[xxi]. Accordingly, we have endeavoured to control for endogeneity due to omitted variables using instruments while also including PUMA fixed effects to control for omitted variables at the PUMA level.

In terms of economic policy, our findings relate to the debate as to whether intervention by Government should be place-based or people-centred. It is apparent from our analysis that what matters are *both* people and places. Despite the limitations of our analysis, we cautiously infer that variation in market potential and employment density does cause variation in resilience, and believe these variables are not simply masquerading as real effects by being correlated with unobserved real effects, and thus there does appear to be a role for place-based intervention. To take just one example, this could come via policies aim at enhancing access to markets and suppliers, both by way of investment in transport infrastructure and by attracting sectors which are best suited to the locally accessible markets and suppliers. Our evidence indicates that boosting market potential in this way would confer additional resilience to residents in more isolated and deprived areas in addition to what could be achieved via channels such as education and training targeted at the individual.

Of course our conclusions are provisional. A limitation of this research is the restricted time period for which we have data, and ideally we would like to have more data pre-2005 and data beyond 2011, but this is not available. Since the impact of the crisis was on-going beyond 2011, it is evident that our data set does not include the full boom-bust cycle, so it would be interesting to study additional data as that becomes available. *Pro tem*, our analysis is of resilience up to 2011, but this may not be the final story. Also it might be argued that because our model of wages is based on a period when the US economy was growing rapidly and the level of our counterfactual wages may be inflated as a consequence. However this would be the same for everyone, and simply have the effect of reducing the level of absolute resilience for everyone by the same amount, so that differences between individuals would remain the same.

Finally, it is worth noting that this paper focuses on the resilience of wages (i.e. those employed) and does not consider the probability of employment. Therefore, while educational attainment may be important for resilience in wages it is also likely to be positively associated with the probability of employment. Given the burgeoning employment crisis in many Western economies, this additional employment-oriented dimension is another important and rather unexplored consideration for individual-level resilience-based studies in the future.

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Table 1: Factors affecting wage levels

| Variable | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Constant | -4.1907*** | -2.0200*** | -1.4061*** |
| | (1.0290) | (1.2904) | (2.5384) |
| Age | 0.0893*** | 0.0894*** | 0.0895*** |
| | (0.0005) | (0.0005) | (0.0006) |
| Age2 | -0.0010*** | -0.0010*** | -0.0010*** |
| | (0.0000) | (0.0000) | (0.0000) |
| Sex | -0.3238*** | -0.3237*** | -0.3238*** |
| | (0.0024) | (0.0024) | (0.0025) |
| Marital Status | | | |
| Married, spouse absent | -0.0816*** | -0.0822*** | -0.0840*** |
| | (0.0044) | (0.0044) | (0.0047) |
| Separated | -0.1305*** | -0.1309*** | -0.1326*** |
| | (0.0034) | (0.0034) | (0.0035) |
| Divorced | -0.0416*** | -0.0425*** | -0.0438*** |
| | (0.0018) | (0.0018) | (0.0020) |
| Widowed | -0.1024*** | -0.1025*** | -0.1029*** |
| | (0.0037) | (0.0037) | (0.0037) |
| Never married/single | -0.1407*** | -0.1416*** | -0.1452*** |
| | (0.0024) | (0.0025) | (0.0032) |
| Ethnicity | | | |
| African American | -0.1415*** | -0.1425*** | -0.1467*** |
| | (0.0039) | (0.0039) | (0.0046) |
| American Indian or Alaska Native | -0.0235 | -0.0254 | -0.0189 |
| | (0.0168) | (0.0154) | (0.0162) |
| Chinese | -0.1636*** | -0.1637*** | -0.1698*** |
| | (0.0089) | (0.0089) | (0.0099) |
| Japanese | 0.0141 | 0.0095 | 0.0049 |
| | (0.0160) | (0.0152) | (0.0151) |
| Other Asian or Pacific Islander | -0.1029*** | -0.1040*** | -0.1087*** |
| | (0.0059) | (0.0058) | (0.0065) |
| Other Race | -0.1268*** | -0.1289*** | -0.1333*** |
| | (0.0046) | (0.0046) | (0.0054) |
| Two major races | -0.0711*** | -0.0730*** | -0.0749*** |
| | (0.0058) | (0.0054) | (0.0056) |
| Three or more major races | -0.0543*** | -0.0585*** | -0.0622*** |
| | (0.0224) | (0.0212) | (0.0208) |
| Education | | | |
| Nursery School to Grade 4 | -0.0398*** | -0.0401*** | -0.0399*** |
| | (0.0150) | (0.0150) | (0.0150) |
| Grade 5, 6, 7 or 8 | 0.0515*** | 0.0518*** | 0.0524*** |
| | (0.0129) | (0.0129) | (0.0129) |

| | | | |
|---|---|---|---|
| Grade 9 | 0.1169*** | 0.1176*** | 0.1188*** |
| | (0.0136) | (0.0136) | (0.0135) |
| Grade 10 | 0.1691*** | 0.1703*** | 0.1723*** |
| | (0.0132) | (0.0132) | (0.0132) |
| Grade 11 | 0.1984*** | 0.1994*** | 0.2017*** |
| | (0.0131) | (0.0131) | (0.0131) |
| Grade 12 | 0.3604*** | 0.3615*** | 0.3633*** |
| | (0.0126) | (0.0126) | (0.0126) |
| 1 year of college | 0.4801*** | 0.4800*** | 0.4806*** |
| | (0.0127) | (0.0127) | (0.0127) |
| 2 years of college | 0.5811*** | 0.5815*** | 0.5825*** |
| | (0.0129) | (0.0129) | (0.0129) |
| 4 years of college | 0.8289*** | 0.8289*** | 0.8274*** |
| | (0.0129) | (0.0129) | (0.0129) |
| 5+ years of college | 1.0976*** | 1.0978*** | 1.0951*** |
| | (0.0130) | (0.0130) | (0.0132) |
| Industry | | | |
| Mining | 0.6401*** | 0.6393*** | 0.6377*** |
| | (0.0172) | (0.0171) | (0.0176) |
| Utilities | 0.4743*** | 0.4727*** | 0.4636*** |
| | (0.0104) | (0.0105) | (0.0118) |
| Construction | 0.3032*** | 0.3010*** | 0.2900*** |
| | (0.0100) | (0.0100) | (0.0120) |
| Manufacturing | 0.3303*** | 0.3290*** | 0.3183*** |
| | (0.0097) | (0.0098) | (0.0117) |
| Wholesale Trade | 0.2910*** | 0.2885*** | 0.2763*** |
| | (0.0098) | (0.0099) | (0.0122) |
| Retail Trade | 0.0249*** | 0.0225*** | 0.0109*** |
| | (0.0096) | (0.0097) | (0.0118) |
| Transportation and Warehousing | 0.2825*** | 0.2803*** | 0.2687*** |
| | (0.0100) | (0.0101) | (0.0123) |
| Information and Communications | 0.3010*** | 0.2986*** | 0.2849*** |
| | (0.0103) | (0.0105) | (0.0132) |
| Finance, Insurance, Real Estate, and Rental and Leasing | 0.3613*** | 0.3586*** | 0.3450*** |
| | (0.0103) | (0.0103) | (0.0131) |
| Professional, Scientific, Management, Administrative, and Waste Management Services | 0.2453*** | 0.2429*** | 0.2293*** |
| | (0.0101) | (0.0102) | (0.0130) |
| Educational, Health and Social Services | 0.1059*** | 0.1038*** | 0.0928*** |
| | (0.0097) | (0.0098) | (0.0117) |
| Arts, Entertainment, Recreation, Accommodations, and Food Services | -0.1483*** | -0.1511*** | -0.1633*** |
| | (0.0104) | (0.0104) | (0.0125) |
| Other Services (Except Public Administration) | -0.1140*** | -0.1163*** | -0.1281*** |
| | (0.0102) | (0.0103) | (0.0125) |

| | | | |
|---|---|---|---|
| Public Administration | 0.2961*** | 0.2943*** | 0.2835*** |
| | (0.0098) | (0.0100) | (0.0119) |
| Year | | | |
| 2005 | 0.0128*** | 0.0134*** | 0.0133*** |
| | (0.0013) | (0.0014) | (0.0015) |
| 2006 | 0.0134*** | 0.0233*** | 0.0260*** |
| | (0.0049) | (0.0061) | (0.0117) |
| Weeks Worked | | | |
| 14-26 | 0.8421*** | 0.8420*** | 0.8419*** |
| | (0.0096) | (0.0096) | (0.0096) |
| 27-39 | 1.3460*** | 1.3460*** | 1.3464*** |
| | (0.0089) | (0.0089) | (0.0089) |
| 40-47 | 1.6707*** | 1.6706*** | 1.6702*** |
| | (0.0085) | (0.0085) | (0.0085) |
| 48-49 | 1.8942*** | 1.8937*** | 1.8929*** |
| | (0.0086) | (0.0086) | (0.0086) |
| 50-52 | 2.0384*** | 2.0384*** | 2.0378*** |
| | (0.0083) | (0.0083) | (0.0083) |
| PUMA-level Variables | | | |
| ln(Employment Density) | 0.0245*** | 0.0318*** | 0.0443*** |
| | (0.0031) | (0.0032) | (0.0080) |
| ln(Market Potential) | 0.9967*** | 0.7848*** | 0.7194*** |
| | (0.0991) | (0.1245) | (0.2454) |
| R2 | 0.4723 | 0.4723 | 0.4719 |
| Obs. | 1988212 | 1988212 | 1988212 |

Note 1: PUMA level dummies are included in the model but not presented here in order to save space.

2: ***, ** and * indicate significance at the 99, 95 and 90 percent level.

3: Estimates based on ACS 2005-2007 for those employed.

4: Model 1 refers to the use of Bartlett's three group method, Model 2 refers to the Le Gallo and Paez (2013) instruments and Model 3 refers to our alternative Le Gallo and Paez (2013) instruments which exclude the weighting of the eignvectors by their respective coefficient.

5: The online appendix to this paper provides further instrumental variable estimations labeled Model 4 and Model 5 where Model 4 refers to Bartlett's three group method and the spatial lags of Bartlett's three group method and finally Model 5 refers to Bartlett's three group method, the spatial lags of Bartlett's three group method and our alternative Le Gallo and Paez (2013) instruments.

Table 2: Factors Affecting Individual Resilience

| Variable | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Constant | -1.4960*** | -1.1459*** | -1.0208*** |
| | (0.1126) | (0.1491) | (0.2742) |
| Age | 0.0023*** | 0.0021*** | 0.0021*** |
| | (0.0001) | (0.0001) | (0.0001) |
| Age2 | -0.0002*** | -0.0002*** | -0.0002*** |
| | (0.0001) | (0.0001) | (0.0001) |
| Sex | 0.0012*** | 0.0016*** | 0.0017*** |
| | (0.0004) | (0.0004) | (0.0004) |
| Marital Status | | | |
| Married, spouse absent | -0.0025** | -0.0023** | -0.0020** |
| | (0.0010) | (0.0010) | (0.0010) |
| Separated | -0.0004 | -0.0002 | 0.0002 |
| | (0.0008) | (0.0008) | (0.0008) |
| Divorced | -0.0024*** | -0.0023*** | -0.0021*** |
| | (0.0004) | (0.0004) | (0.0004) |
| Widowed | 0.0016** | 0.0018*** | 0.0019*** |
| | (0.0007) | (0.0007) | (0.0007) |
| Never married/single | -0.0078*** | -0.0075*** | -0.0068*** |
| | (0.0004) | (0.0004) | (0.0005) |
| Ethnicity | | | |
| African American | -0.0011** | -0.0007 | 0.0002 |
| | (0.0006) | (0.0006) | (0.0006) |
| American Indian or Alaska Native | 0.0047 | 0.0043 | 0.0024 |
| | (0.0036) | (0.0029) | (0.0025) |
| Chinese | 0.0016 | 0.0022* | 0.0036*** |
| | (0.0013) | (0.0013) | (0.0014) |
| Japanese | -0.0075*** | -0.0068** | -0.0059** |
| | (0.0032) | (0.0030) | (0.0030) |
| Other Asian or Pacific Islander | -0.0010 | -0.0005 | 0.0005 |
| | (0.0009) | (0.0009) | (0.0010) |
| Other Race | 0.0022*** | 0.0025*** | 0.0033*** |
| | (0.0008) | (0.0008) | (0.0009) |
| Two major races | -0.0068*** | -0.0064*** | -0.0060*** |
| | (0.0014) | (0.0014) | (0.0014) |
| Three or more major races | -0.0039 | -0.0034 | -0.0027 |
| | (0.0040) | (0.0038) | (0.0038) |
| Education | | | |
| Nursery School to Grade 4 | 0.0117*** | 0.0117*** | 0.0117*** |
| | (0.0030) | (0.0029) | (0.0029) |
| Grade 5, 6, 7 or 8 | 0.0038 | 0.0037 | 0.0036 |
| | (0.0025) | (0.0025) | (0.0025) |
| Grade 9 | 0.0006 | 0.0004 | 0.0003 |

| | | | |
|---|---|---|---|
| | (0.0026) | (0.0026) | (0.0026) |
| Grade 10 | 0.0037 | 0.0034 | 0.0030 |
| | (0.0026) | (0.0026) | (0.0026) |
| Grade 11 | 0.0062*** | 0.0058** | 0.0053** |
| | (0.0026) | (0.0025) | (0.0025) |
| Grade 12 | 0.0063*** | 0.0057** | 0.0052** |
| | (0.0024) | (0.0024) | (0.0023) |
| 1 year of college | 0.0037 | 0.0030 | 0.0027 |
| | (0.0024) | (0.0024) | (0.0023) |
| 2 years of college | 0.0115*** | 0.0105*** | 0.0101*** |
| | (0.0024) | (0.0024) | (0.0024) |
| 4 years of college | 0.0137*** | 0.0126*** | 0.0125*** |
| | (0.0024) | (0.0024) | (0.0024) |
| 5+ years of college | 0.0174*** | 0.0159*** | 0.0161*** |
| | (0.0025) | (0.0024) | (0.0024) |
| Industry | | | |
| Mining | 0.0077*** | 0.0067*** | 0.0067*** |
| | (0.0022) | (0.0022) | (0.0022) |
| Utilities | 0.0003 | -0.0001 | 0.0014 |
| | (0.0015) | (0.0015) | (0.0016) |
| Construction | -0.0022 | -0.0023 | -0.0004 |
| | (0.0015) | (0.0015) | (0.0017) |
| Manufacturing | -0.0037*** | -0.0039*** | -0.0019 |
| | (0.0014) | (0.0014) | (0.0016) |
| Wholesale Trade | -0.0062*** | -0.0062*** | -0.0040*** |
| | (0.0015) | (0.0015) | (0.0018) |
| Retail Trade | -0.0125*** | -0.0121*** | -0.0099*** |
| | (0.0014) | (0.0014) | (0.0017) |
| Transportation and Warehousing | -0.0074*** | -0.0074*** | -0.0053*** |
| | (0.0015) | (0.0015) | (0.0018) |
| Information and Communications | -0.0097*** | -0.0096*** | -0.0071*** |
| | (0.0016) | (0.0017) | (0.0020) |
| Finance, Insurance, Real Estate, and Rental and Leasing | -0.0076*** | -0.0077*** | -0.0052*** |
| | (0.0015) | (0.0015) | (0.0018) |
| Professional, Scientific, Management, Administrative, and Waste Management Services | -0.0090*** | -0.0088*** | -0.0063*** |
| | (0.0015) | (0.0015) | (0.0018) |
| Educational, Health and Social Services | -0.0124*** | -0.0122*** | -0.0102*** |
| | (0.0014) | (0.0014) | (0.0017) |
| Arts, Entertainment, Recreation, Accommodations, and Food Services | -0.0116*** | -0.0111*** | -0.0087*** |
| | (0.0015) | (0.0015) | (0.0018) |
| Other Services (Except Public Administration) | -0.0144*** | -0.0137*** | -0.0114*** |
| | (0.0015) | (0.0016) | (0.0018) |
| Public Administration | -0.0028** | -0.0028** | -0.0009 |

| | | | |
|---|---|---|---|
| | (0.0014) | (0.0014) | (0.0017) |
| Weeks Worked | | | |
| 14-26 | 0.0547*** | 0.0521*** | 0.0514*** |
| | (0.0026) | (0.0026) | (0.0025) |
| 27-39 | 0.0672*** | 0.0637*** | 0.0626*** |
| | (0.0025) | (0.0024) | (0.0024) |
| 40-47 | 0.0823*** | 0.0781*** | 0.0770*** |
| | (0.0024) | (0.0024) | (0.0023) |
| 48-49 | 0.0799*** | 0.0755*** | 0.0744*** |
| | (0.0025) | (0.0024) | (0.0024) |
| 50-52 | 0.1025*** | 0.0976*** | 0.0964*** |
| | (0.0023) | (0.0022) | (0.0022) |
| PUMA-level Variables | | | |
| ln(Employment Density) | -0.0015*** | -0.0015*** | -0.0036*** |
| | (0.0003) | (0.0003) | (0.0010) |
| ln(Market Potential) | 0.1136*** | 0.0825*** | 0.0724*** |
| | (0.0108) | (0.0143) | (0.0263) |
| R2 | 0.0578 | 0.0536 | 0.0530 |
| Obs. | 671472 | 671472 | 671472 |
| F-tests | | | |
| Marital Status | 335.79*** | 312.65*** | 198.30*** |
| Age | 547.39*** | 518.91*** | 508.42*** |
| Race | 49.54*** | 49.25*** | 51.06*** |
| Education | 646.32*** | 581.61*** | 502.66*** |
| Industry | 951.56*** | 911.74*** | 754.99*** |
| Weeks Worked | 4443.85*** | 4271.08*** | 4271.91*** |
| PUMA Market Potential and Employment Density | 124.65*** | 35.61*** | 15.71*** |

Note 1: PUMA level dummies are included in the model but not presented here in order to save space.

2: ***, ** and * indicate significance at the 99, 95 and 90 percent level.

3: standard errors are in parentheses, p-values for F-tests are in square brackets.

4: Model 1 refers to the use of Bartlett's three group method, Model 2 refers to the Le Gallo and Paez (2013) instruments and Model 3 refers to our alternative Le Gallo and Paez (2013) instruments which exclude the weighting of the eignvectors by their respective coefficient.

5: The online appendix to this paper provides further instrumental variable estimations labeled Model 4 and Model 5 where Model 4 refers to Bartlett's three group method and the spatial lags of Bartlett's three group method and finally Model 5 refers to Bartlett's three group method, the spatial lags of Bartlett's three group method and our alternative Le Gallo and Paez (2013) instruments.

Figure 1: Log of Market Potential 2007

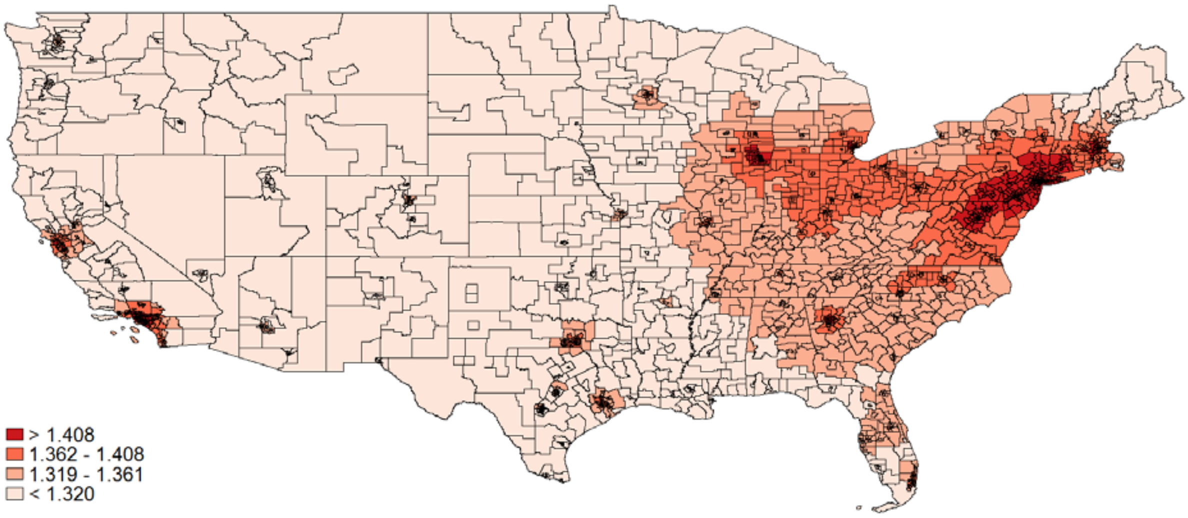


Figure 2: Log of Employment Density in 2007

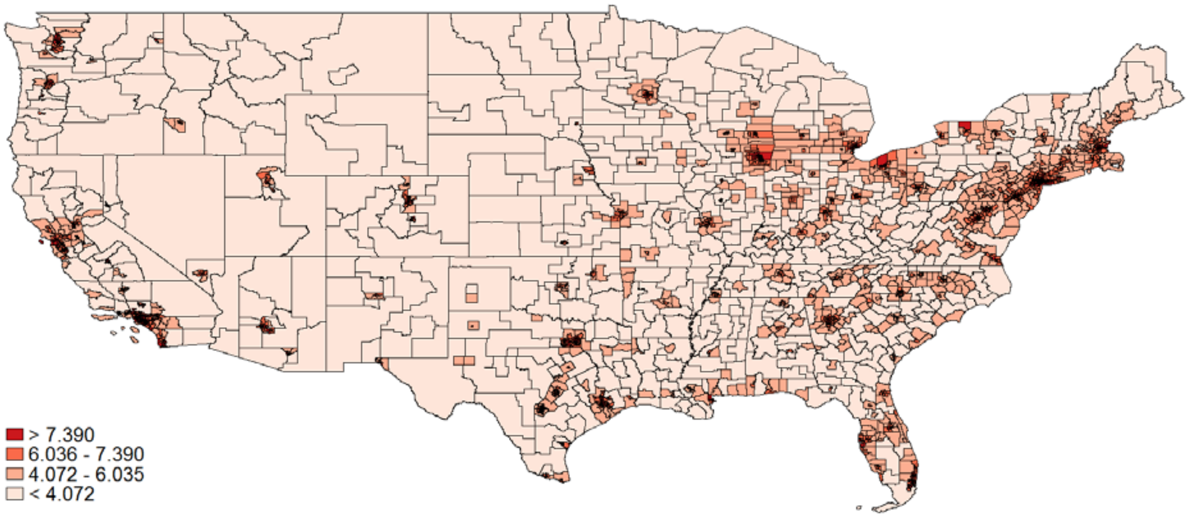
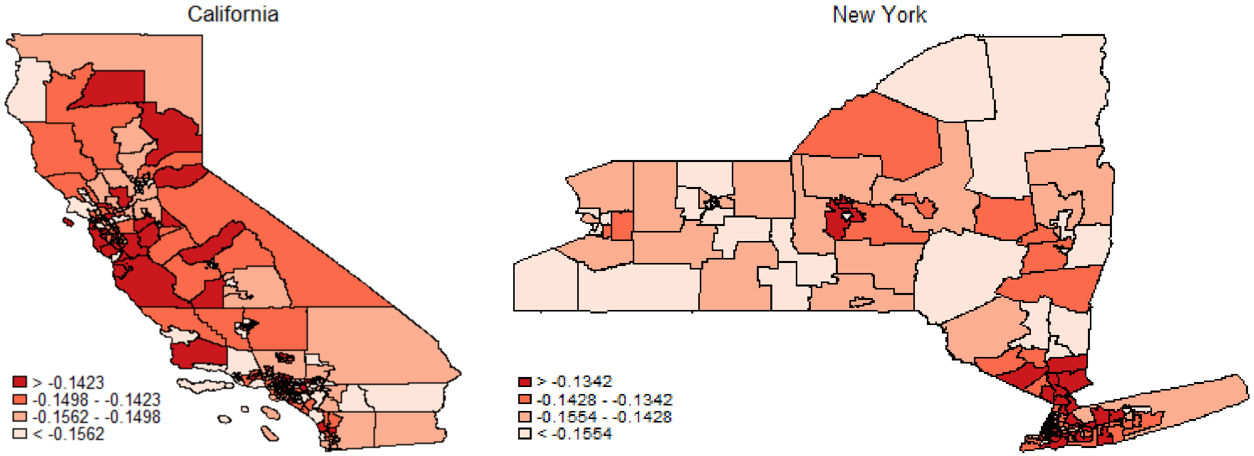


Figure 3: Proportional Resilience by States



[i] There are about 2100 PUMAs compared with approximately 3100 counties and county equivalents in the USA.

[ii] This temporary versus permanent debate relates closely to the concept of hysteresis, as discussed for example by Romer (2001) and Blanchard and Summers (1987).

[iii] The exact functional form for these independent variables is discussed extensively in Heckman et al. (2003).

[iv] These take the form of a series of dummy variables representing PUMA 2 to *K* (with PUMA 1 being the base area).

[v] In practice we do not think we have omitted 'ability' as a variable, given the specification of our model.

[vi] With positive intra-PUMA dependence, not allowing for this will result in smaller standard errors than otherwise and hence larger t-ratios, leading to a higher than nominal (say 0.05) proportion of Type I errors.

[vii] Also endogeneity-inducing simultaneity may occur because of the theoretical link between wages and market potential (since wages will determine income which is a determinant of market potential).

[viii] This is done separately for each time period, with the set of instruments then concatenated to create a single instrument covering all periods.

[ix] The online appendix to this paper also provides the estimates obtained as a result of applying additional instrumental variables, namely Bartlett's three group method combined with the spatial lags of the three groups, and these also combined with our alternative Le Gallo and Paez (2013) instruments. These instruments produce results similar to those detailed here in the paper.

[x] Note that we adjust the actual wage levels to 2007 price levels.

[xi] ACS files from 2000-2004 did not include the PUMA variables.

[xii] In NEG theory, the economy is divided into the *M* sector under a monopolistic competition market structure, and the competitive sector (*C*).

[xiii] Los Angeles and San Francisco.

[xiv] While the Sargan test can be used to test for the validity of instruments a number of requirement must hold for this test to be valid. Firstly, the model must be overidentified and secondly the errors must be iid. In our case our models are not overidentified and in all cases our model specification entails non-iid errors. Therefore, the application of the Sargan test to our models would be inappropriate (Stata 2009).

[xv] The reference sector for industries is agriculture, forestry and fishing.

[xvi] Note that we use the estimates of column 1 in Table 1 in this section but that our results do not vary if we use the estimates from any of the other columns in Table 1.

[xvii] Using a row standardised matrix containing the inverse of the distance in kilometres from the 'centre point' of each region.

[xviii] Space considerations do not allow a larger number of maps, but these are available from the authors.

[xix] To save space we do not give full details here of this ancillary regression, which are available from the authors on request.

[xx] This is shown as the coefficient on age is positive while the coefficient on age$^2$ is negative indicating a non-linear, inverse U-shaped relationship.

[xxi] This is somewhat difficult given a pseudo-panel.