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REGIONAL VARIATIONS IN LABOR DEMAND ELASTICITY: EVIDENCE FROM U.S. COUNTIES

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ABSTRACT. We use a large panel dataset covering the period 1988–2010 to estimate county specific own-wage elasticity of labor demand in the U.S. for four highly aggregated industries: construction, finance/insurance/real-estate/service, manufacturing, and retail trade. Our estimation of a random parameter panel data model yields significant evidence of spatial variations in wage elasticity of labor demand. We relate the spatial variation in elasticity to differences in county characteristics like industry specialization, industry competition, levels of natural amenity and urbanization. Using a regression discontinuity approach we also find that probusiness states have higher labor demand elasticity.

1. INTRODUCTION

The estimation of wage elasticity of labor demand has attracted significant attention in empirical labor economics. Hamermesh (1993) provides an exhaustive review of the early research in this field. A more recent survey can be found in Lichter, Peichi, and Siegloch (2014) who tabulate 151 studies conducted between 1980 and 2012 on 37 different countries. Most studies listed in these articles estimate wage elasticity of labor demand for one sector or industry, in particular the manufacturing sector, and assume no spatial variation in elasticity. In this paper, we document spatial heterogeneity in U.S. labor demand elasticity by estimating industry-county elasticity for four aggregated industries[1]: construction, finance/insurance/real-estate/service, manufacturing, and retail trade. There are other studies which also find significant spatial heterogeneity in U.S. labor market outcomes. For example, after a comprehensive survey of the local labor market literature, Moretti (2011) catalogs spatial variations in nominal wages, real wages, productivity, and innovation across U.S. labor markets. He also finds evidence that these variations have persisted over many decades.

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[1]Together these four industries account for, on an average, about 87 percent of annual employment in the private nonfarm sector in the U.S.

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We use a large panel dataset based on the County Business Patterns and a two-step procedure to estimate industry-county labor demand elasticity. In step 1, we specify a random parameter panel data model, where we assume that industry-county labor demand elasticity is not constant, but has a lognormal distribution in the population of counties. The lognormal distribution ensures that the absolute value of labor demand elasticity is always positive. We estimate the parameters of this model using the method of Maximum Simulated Likelihood (MSL). Once we have information regarding the distributions of labor demand elasticity, in step 2, we retrieve county-level estimates using Bayes' rule. We believe that this two-step approach provides an alternative method for estimating spatially heterogeneous parameters.[2] In the extant literature on labor demand elasticity, variation in elasticity is usually introduced either by estimating separate regression models on subsets of data (Slaughter, 2001), or by interacting the elasticity parameter with some spatially heterogeneous variable (Hasan, Mitra, and Ramaswamy, 2007). In our approach, we do not need to subset our data in estimation, and more importantly, we do not need to make any assumption regarding which variable to interact with the elasticity parameter. A drawback of our approach is that it is computationally more challenging than linear models; plus we also need to make an assumption regarding the distribution of parameters.

The labor demand elasticity in the four industries are distributed lognormal with the following means and standard deviations:[3] 0.15 (0.13) for construction, 0.005 (0.05) for finance/insurance/real-estate/service, 0.21 (0.38) for manufacturing, and 0.09 (0.25) for retail trade. We find that the scale parameter of the lognormal distribution is statistically significant for all four industries which confirm the presence of spatial heterogeneity in labor demand elasticity. How do our results compare with existing estimates in the literature on labor demand elasticity? Lichter et al. (2014) report a mean value of 0.50 (0.77) for overall labor demand elasticity. In their analysis they classify elasticity estimates based on a number of factors—time period, dataset, workforce, industry, and country—and report mean values for each group. In the short run, the mean value of elasticity is 0.21 (0.40) while in the long run it is 0.34 (0.47). At the industry level the mean value of elasticity is 0.53 (0.49), 0.04 (0.20), and 0.05 (0.23) in the manufacturing, service, and construction sectors, respectively. They do not report any estimates for the retail trade sector. Our average elasticity estimates for all the industries fall in the ranges reported in Lichter et al. (2014) albeit they are on the lower side of the ranges.

Our county level estimates of labor demand elasticity allow us to test if they are related to other features of the spatial landscape of the U.S. economy. In particular, we test if labor demand elasticity can be classified on the basis of natural amenity, industry-county specialization and competition, urbanization, and government policies (Glaeser et al., 1992; Holmes and Stevens, 2004). Our findings can be summarized as follows:

(1) Counties with better natural amenity have higher labor demand elasticity.

(2) More industry-county specialization and competition reduces labor demand elasticity.

(3) Urbanization and labor demand elasticity is negatively related.

(4) Counties which belong to more probusiness states have higher labor demand elasticity.

[2]A popular and widely used nonparametric method that deals with estimation of spatially heterogeneous parameters is called Geographically Weighted Regression (GWR) (Brunsdon, Fotheringham, and Charlton, 1996). McMillen (2010) summarizes the application of GWR and other parametric and semi-parametric methods in regional science and urban economics.

[3]Standard deviation in parenthesis.

The last result is found using a regression discontinuity design described in Holmes (1998),[4] where probusiness states are defined as those states which have adopted the right-to-work law.

Our findings have important policy implications. In the U.S., federal, state, and local governments intervene—in a variety of ways—in labor markets. For example, wage subsidy programs seek to boost earnings and employment among the weaker sections of society (Katz, 1996). In addition, state and local governments implement policies to try and attract firms by providing them a variety of incentives, to either relocate, or open a new establishment in their jurisdiction. Bartik (1991) provides a comprehensive list of such policies and Bartik (2002) claims that these policies costs approximately $30–40 billion to implement. It is easy to see in a partial equilibrium setting with perfectly elastic labor supply, that ceteris paribus, in response to a wage subsidy program, counties with higher labor demand elasticity will generate larger employment gains as compared to counties with lower labor demand elasticity. The entry of a new firm and a subsequent output shock, will however, have the opposite effect, as labor demand will rise more in a county with lower labor demand elasticity as compared to a county with higher labor demand elasticity. This means that these policies need to be adjusted spatially to generate similar effects across regions. In addition, the differential effect of output on employment is also useful for investigating how employment levels in different regions reacts differently during a recession.[5] Our results imply that differences in regional unemployment levels might arise not only because different regions have different industry compositions, but also because different regions have different labor demand elasticity.

Policy recommendations based on a partial equilibrium framework, however, can be misleading, since we ignore the effects of other markets, in particular the housing market.[6] To get accurate results we must rely on general equilibrium models. Partridge and Rickman (2010) provide a thorough discussion on the increasing use of CGE models to assess local regional development policies. Our industry-county labor demand estimates can be used to calibrate labor demand functions in such CGE models and perform policy evaluations.

This paper proceeds as follows. In Section 2, we describe the data. Section 3 presents the theory behind labor demand elasticity and outlines the estimation procedures. Section 4 discusses the estimation results and classifies the elasticity estimates based on county and industry characteristics mentioned earlier. We conclude in Section 5 by summarizing our results and pointing to some future extension.

2. DATA

We use the County Business Patterns (CBP) dataset from the period 1988–2010 to get annual industry level data on total employees and total payroll for counties in the conterminous U.S. Data in the CBP is available at various industry aggregation levels. For reasons we explain below we use data based on the two-digit industry classification system—this is the highest industry aggregation level available in the CBP. We then further categorize (see Table 1) a subset of these two-digit industries into four major

[4]We are grateful to Professor Thomas Holmes for sharing his data with us.

[5]See Fingleton, Garretsen, and Martin (2012) and Curtis (2014) for a discussion of this issue.

[6]The Rosen-Roback (Rosen, 1979; Roback, 1982) model is a popular spatial general equilibrium model which illuminates the tight link between the labor market and the housing market in a region. See Glaeser and Gottlieb (2009) for a thorough discussion of the Rosen-Roback model.

TABLE 1: Descriptive Statistics

	$N \times T$	Total Counties	Metro Counties	Nonmetro Counties: Urban	Nonmetro Counties: Rural	Mean	Std. Dev.	SIC	NAICS
Construction									
Employees	64,064	3,046	818	1,489	739	2,043	6,741	**15**	23
Real wage						20	6		
Real output						2,381	3,320		
Measure of specialization						1.19	0.56		
Measure of competition						1	0.46		
Bartik's IV						0.05	0.03		
Financial/insurance/real estate/service									
Employees	69,389	3,068	818	1,489	761	15,104	64,721	**60, 70**	51, 52, 53, 54, 55, 56, 61, 62, 81
Wage						23	12		
Output						38,321	61,737		
Measure of specialization						1.05	0.21		
Measure of competition						1	0.33		
Bartik's IV						0.05	0.03		
Manufacturing									
Employees	59,577	2,950	817	1,476	657	6,104	19,855	**20**	31–33
Wage						24	8		
Output						7,761	14,794		
Measure of specialization						1.34	0.74		
Measure of competition						1	0.54		
Bartik's IV						0.05	0.03		
Retail trade									
Employees	69,707	3,071	818	1,489	764	7,854	25,580	**52**	44, 45, 71, 72
Wage						10	2		
Output						5,170	8,775		
Measure of specialization						1.06	0.27		
Measure of competition						1	0.29		
Bartik's IV						0.04	0.03		

Notes: N is county, T is year. Employees are mid March workers from the County Business Patterns. Wage is expressed in terms of US$(2010) per hour and is calculated using the formula: $Wage_t = (\frac{CPI_{2010}}{CPI_t})(\frac{First\ quarter\ payroll_t}{480 \times Employees})$; first-quarter payroll is from the County Business Patterns; CPI is consumer price index. Output is in millions of US$(2010) and is calculated using the formula: $Output_t = (\frac{PPI_{2010}}{PPI_t})(\frac{Employees_{ict}}{\sum_{c'} Employees_{ic't}})GSP_{ist}$, where GSP_{ist} is Gross state product from the Bureau of Economic Analysis; *PPI* is producer price index. *SIC* and *NAICS* refer to the Standard Industry Classification and National Industry Classification systems, respectively. The SIC was followed until 1997 after which the NAICS was adopted by the Census Bureau in tabulating the County Business Patterns.

industry groups—construction, finance/insurance/real-estate/service, manufacturing, and retail trade.[7]

The CBP has strength and weaknesses (Isserman and Westervelt, 2006). Its advantages are that it is establishment-based[8] making it ideal for spatial analysis, highly accurate,[9] industrially detailed, and is available every year since 1964. The CBP, however, has its drawbacks. For one thing, it does not include all employment.[10] In addition, the industry classification system used in the CBP changes periodically. During 1988–2010, the CBP followed two different industry classification systems—the Standard Industry Classification (SIC) system for the period leading up to 1997 and the North American Industry Classification System (NAICS) thereafter. However, the biggest problem with the CBP is data suppression due to confidentiality reasons. This problem rises with industrial detail and in such cases the CBP provides an interval for industry employment level, but sets payroll data equal to zero.

The choice of using the two-digit industry classification system makes our industry definition less sensitive to changes in the industry classification system but more importantly it minimizes the effects of data suppression in our analysis. We now describe some statistics regarding data suppression at the two-digit industry level. In the construction industry 9 percent of 71,153 observations (an observation is a two-digit industry-county-year combination) suffer from data suppression and 96 percent of the missing data are from nonmetro counties (see Appendix A for definition of nonmetro counties). The finance/insurance/real-estate/service industry has 400,534 observations, 21 percent of which have missing data, and 79 percent of the missing data belong to nonmetro counties. The manufacturing sector has 70,314 observations, 14 percent of which have missing data, and 92 percent of the missing data belong to nonmetro counties. Finally, in the retail trade sector, 13 percent of 150,001 observations have missing data and 83 percent of the missing data belong to nonmetro counties. The finance/insurance/real-estate/service and retail trade industry groups have significantly larger number of observations than the construction and manufacturing sectors since the former two are made up of significantly more two-digit industries (see Table 1).

While we lose a large number of observations due to data suppression, a more important question for our empirical analysis is to know the number of industry employees we fail to include due to missing data. In the CBP, while data suppression affects individual two-digit industries, it does not affect the reporting of total employment across all industries for a county-year combination.[11] This allows us to calculate the number of employees we lose due to data suppression. Our calculation shows that, on average, every year we lose about 1 percent of total employment. This means that the observations with the missing employment data can be safely dropped from our analysis without biasing our results—the remaining data set is able to capture 99 percent of all employment fluctuations recorded in the CBP. After dropping the observations with missing employment data we aggregate the two-digit industry data into our four major industry groups based

[7]We leave out agriculture, mining, transportation, and wholesale trade from our analysis.

[8]Establishments, according to the Census Bureau are physical locations of economic activity.

[9]The accuracy of the CBP comes from the fact that it is based on administrative records of the Internal Revenue Service, the Social Security Administration, and the Bureau of Labor Statistics.

[10]It covers private, nonfarm employment, but ignores agricultural production employees, majority of government employees, self-employed individuals, employees of private households, and railroad employees. It only counts full- and part-time employees on the payroll in the mid-March period. This introduces a seasonal component in the data for certain industries.

[11]As Isserman and Westervelt (2006) reports, in 2002, only 77,331 total jobs were subject to suppression out of 112.4 million, a negligible quantity.

on the classification in Table 1. This yields a datasets consisting of 64,832; 70,166; 60,331; and 70,484 observations for the construction, finance/insurance/real-estate/service, manufacturing, and retail trade industries, respectively.

The industry datasets have an unbalanced panel structure as not all counties appear every year in each industry dataset. The construction, finance/insurance/real-estate/service, manufacturing, and retail trade datasets contain 3,078; 3,100; 2,982; and 3,103 distinct counties. The average length of appearance for each county in these four datasets are 21, 22, 20, and 22 years, respectively. In the period 1988–2010 there were 3,114 distinct counties in the conterminous U.S. implying that the industry datasets cover on average 98 percent of counties and these counties on average appear 90 percent of the time. As mentioned earlier the counties absent from the industry datasets are mostly nonmetro counties with sparse employment levels.

The CBP follows the U.S. census definition for counties: the independent cities in Virginia are treated as separate counties. This is unlike cities in other states which are part of the counties in which they are located. Following Holmes (1998) we merge the independent cities in Virginia with the counties that surround them—this definition of counties comes from the Regional Economic Information System (REIS). This consolidation of cities in Virginia with surrounding counties reduces the number of observations in the industry datasets. Now construction, finance/insurance/real-estate/service, manufacturing, and retail trade have 64,064; 69,389; 59,577; 66,707 observations, respectively.

We calculate the industry wage rate by dividing first quarter payroll by the total number of mid-March employees (Slaughter, 2001). The exact formula is shown below where i, c, t denote industry, county, and year, respectively:

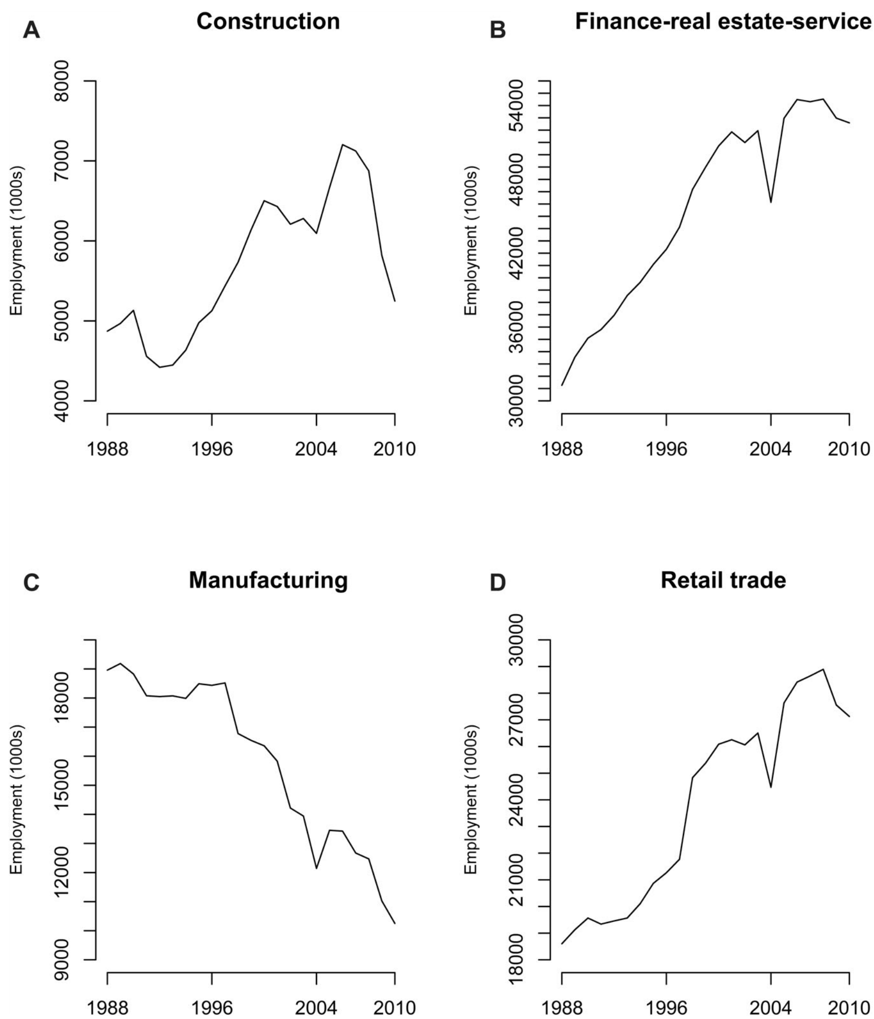
$$w_{ict} = \left(\frac{CPI_{2010}}{CPI_i} \times \frac{Total\ first\ quarter\ payroll_{ict}}{Employees_{ict}} \right) \div 480. \tag{1}$$

The division by 480 indicates that we assume that an average worker is employed for 480 hours during the first quarter. CPI is the consumer price index series obtained from the Bureau of Labor Statistics (BLS).

We obtain state level industry GDP from the Bureau of Economic Analysis (BEA). We assume that a county's industry share in its state-industry GDP (SGDP) is equal to the county's industry employment share in its state-industry employment. Using this assumption, we impute county industry GDP, which gives us a measure of industry demand conditions. The exact formula is shown below; PPI is the producer price index obtained from the BLS

$$Y_{ict} = \left(\frac{PPI_{2010}}{PPI_i} \times \frac{Employees_{ict}}{\sum_{c'} Employees_{ic't}} \times Gross\ state\ product_S \right). \tag{2}$$

In our sample the count of employees grew 29 percent from 73,708,553 in 1988 to 95,249,830 in 2010. In 1988, the distribution of employment among the four industries in our sample is: construction 7 percent, finance/insurance/real-estate/service 42 percent, manufacturing 26 percent, and retail trade 25 percent. In the next 23 years the employment levels in the construction, finance/insurance/real-estate/service, and retail trade industries registered growth rates of 8 percent, 68 percent, and 46 percent, respectively. The manufacturing sector during the same period experienced a fall in employment of around 46 percent. This means that in 2010 the distribution of employment among the four industries stood at: construction 6 percent, finance/insurance/real-estate/service 55 percent, manufacturing 11 percent, and retail trade 28 percent. In other words, in the 23 years period, the finance/insurance/real-estate/service and retail sectors increased their share in total employment mainly at the expense of the manufacturing sector. During the same time period, real output of the construction, finance/insurance/real-



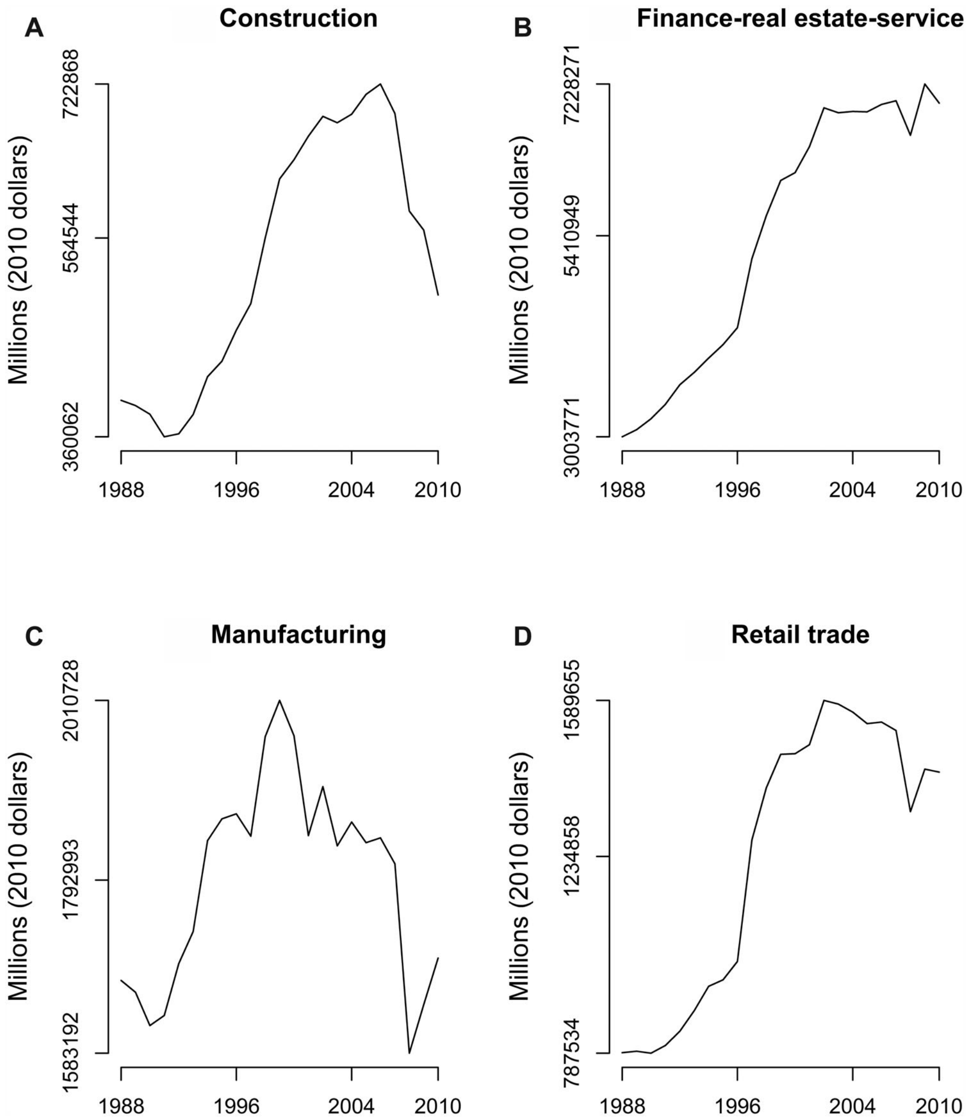
Note: Employment data is from County Business Patterns.

FIGURE 1: Total National Industry Employment.

estate/service, manufacturing, and retail trade industries grew by 27 percent, 131 percent, 1 percent, and 79 percent, respectively. Figures 1 and 2 graph the evolution of total national employment and average national real output in our sample.

The national average real wage rates (US$ per hour) in 1988 in the construction, finance/insurance/real-estate/service, manufacturing, and retail trade industries were 20, 19, 25, and 10, respectively. In 2010, they stood at 21, 26, 24, and 10, respectively. Therefore, in the period 1988–2010 employees in the construction and finance/insurance/real-estate/service saw modest growth in real wage rates, employees in manufacturing and retail trade actually witnessed a decline in their real wage rates. A major reason for this is the great recession that hit the U.S. in 2008. Figure 3 plots the national annual average values of real wage rates for the four industries.

Following Blanchard and Katz (1992) we calculate two measures which can shift the labor demand curve by affecting industry-county output. The first measure described

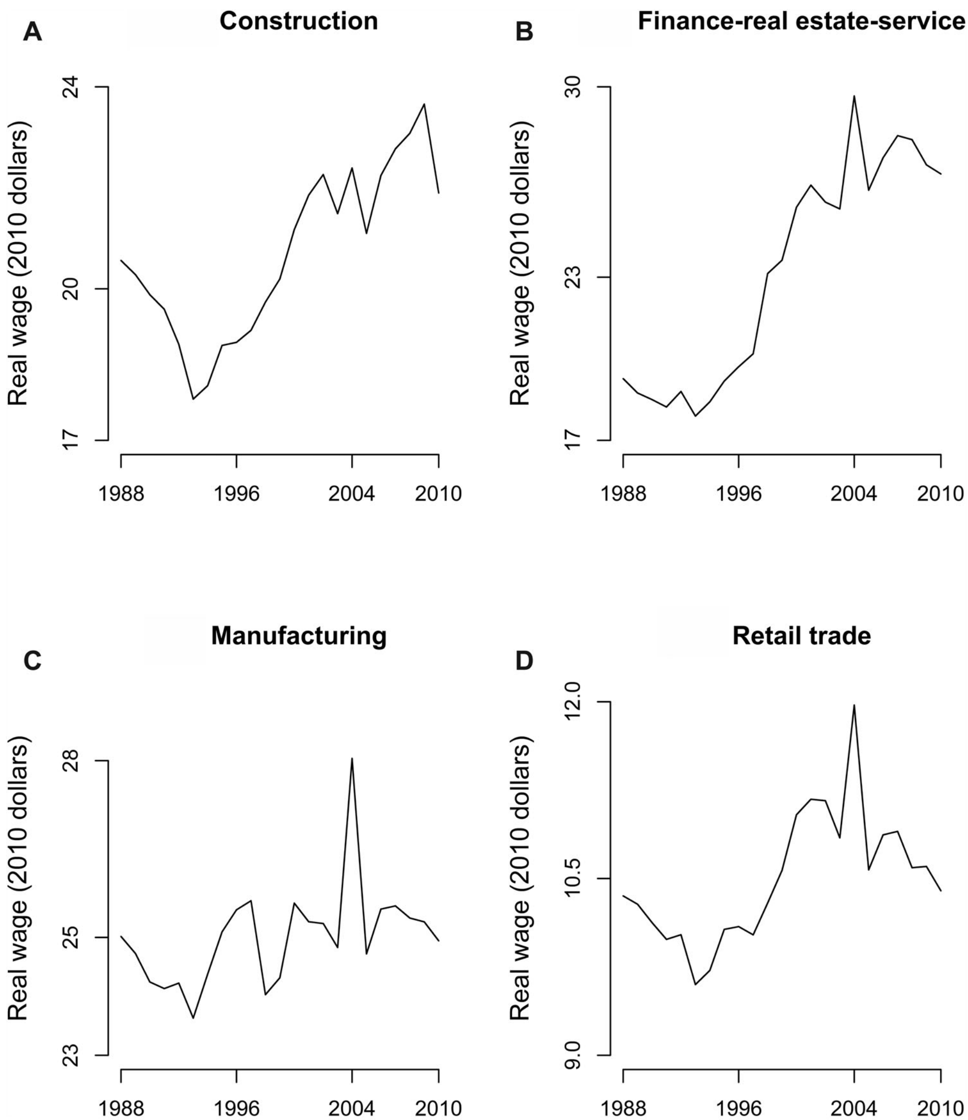


Notes: Industry real output is calculated by deflating nominal output using the Producer Price Index. Nominal output data is from the Bureau of Economic Analysis (BEA). Producer Price Index data is from the Bureau of Labor Statistics.

FIGURE 2: National Industry Total Real Output.

in Equation (3) predicts output change for an industry-county, based on national output trends—it is called Bartik's IV, following Bartik (1991) who popularized its use as an instrument. In Equation (3), $Y\_i(-c)t$ is the national output of industry i less the industry output in county c. Bartik's IV is therefore the weighted average of changes in national industry outputs where the weights are industry-county employment shares

$$(3) \qquad Bartik\_IV_{ct} = \frac{\sum_i Employees_{ict}\left[\ln\left(Y_{i(-c)t}\right) - \ln\left(Y_{i(-c)t-1}\right)\right]}{\sum_i Employees_{ict}}.$$



Notes: National real wage is the employment share weighted average of industry-county real wages. Real wage is calculated by deflating nominal wage using the Consumer Price Index (CPI). Nominal wage data is calculated by dividing industry-county first-quarter payroll data from the County Business Patterns by 480. CPI data is from Bureau of Labor Statistics

FIGURE 3: National Industry Real Wage (US$ per Hour).

The second measure is dollar amounts in federal defense contracts received by each state in the period 1988–2010. Data on federal defense contracts from the U.S. Census Bureau are not available for every year, so the missing years were imputed using a linear interpolation method. In Appendix D plot (c), we show a Box-plot for the federal defense contract.

In this paper we not only estimate industry-county labor demand elasticity, but also attempt to see if they are related to county characteristics. In particular we measure industry-county specialization and competition, and levels of county urbanization and natural amenity. Our measure of industry-county specialization and competition is borrowed from Glaeser et al. (1992) who also used CBP data in their analysis. An industry-county's degree of specialization is measured by using the ratio of the industry-county's share in total county employment to the industry's national share in total national employment (Equation (4)). This measure is applicable for broad geographical units (Holmes, 2004) like counties, but unsuitable for more disaggregate geographical units where a measure like the Ellison-Glaeser index (Ellison and Glaeser, 1997) is more appropriate (Equation (4)). Equation (5) describes the industry-county competition where we take the ratio of firms per worker in an industry-county to firms per worker in the industry at the national level. In both cases values greater than one indicate that the industry-county is more specialized and is characterized by more competition than at the national level. See Table 1 for descriptive statistics on these variables.

$$(4) \qquad Specialization = \frac{\frac{Industry\ employment\ in\ county}{Total\ employment\ in\ county}}{\frac{Industry\ employment\ in\ the\ U.S.}{Total\ employment\ in\ the\ U.S.}},$$

$$(5) \qquad Competition = \frac{\frac{Firms\ in\ industry\ in\ county}{Workers\ in\ industry\ in\ county}}{\frac{Firms\ in\ industry\ in\ the\ U.S.}{Workers\ in\ industry\ in\ the\ U.S.}}.$$

To measure the levels of county urbanization and natural amenity we use the urbanization code and natural amenity scale developed by the United States Department of Agriculture (USDA).[12] Based on this urbanization code we classify counties into three groups: metro counties, nonmetro counties that are urban and nonmetro counties that are rural. In Appendix D plot (d), we show a density plot for the natural amenity scale.

In this paper, we also investigate the effect of government policies on industry-county labor demand elasticity. In particular, we test if the presence of probusiness policies raises or lowers labor demand elasticity. We classify states as probusiness if they have implemented a right-to-work law, since Holmes (1998) claims that such states also tend to have a host of other probusiness policies. Table 2 lists the states that have adopted the right-to-work law along with the year of adoption.[13]

If a union is certified at a place of work, then an employee might be required to join the union or pay membership dues. This practice deals with the free rider problem where a worker does not pay the cost of negotiation (membership fee, wage loss during the negotiation period if a strike is called), but enjoys the benefits made possible by negotiations between management and union. A right-to-work law removes the requirement of being a union member in order to gain employment, or paying membership fees even if the nonunion member worker will enjoy the benefits arising from the union's negotiations with the management (Leap, 1995). The right-to-work law therefore can be viewed as probusiness since it weakens the power of unions and strengthen employers' position in bargaining.

[12]We would like to thank a referee for pointing us to this data source.

[13]Texas and Oklahoma implemented the right-to-work law in 1993 and 2001, respectively, which straddle our study period, and Indiana and Michigan implemented them in 2012, which falls outside our study period, we assume for our empirical analysis that these states are probusiness. This is because, the eventual implementation of this law in these states signify the presence of other probusiness policies (1998).

TABLE 2: States with Right-to-Work Laws

State	Year of Statue Enactment	Year of Constitutional Amendment
ALABAMA	1953	
ARIZONA	1947	1946
ARKANSAS	1947	1944
FLORIDA	1943	1968
GEORGIA	1947	
IDAHO	1985	
INDIANA	2012	
IOWA	1947	
KANSAS		1958
LOUISIANA	1976	
MICHIGAN	2012	
MISSISSIPPI	1954	1960
NEBRASKA	1947	1946
NEVADA	1951	1952
NORTH CAROLINA	1947	
NORTH DAKOTA	1947	1948
OKLAHOMA	2001	2001
SOUTH CAROLINA	1954	
SOUTH DAKOTA	1947	1946
TENNESSEE	1947	
TEXAS	1993	
UTAH	1955	
VIRGINIA	1947	
WYOMING	1963	

Note: Data is from the National Conference of State Legislatures.

3. WAGE ELASTICITY OF LABOR DEMAND: THEORY AND ESTIMATION

Following Hamermesh (1993), the total wage elasticity of labor demand (η'_{LL}) can be written as

$$\frac{\delta \ln L(w,Y)}{\delta \ln w} = \left(\eta'_{LL}\right) = -\underbrace{[1-s_L]\sigma}_{Substitution\ effect} - \underbrace{s_L \eta_D}_{Scale\ effect}, \tag{6}$$

where, s_L is the share of labor in total revenue, σ is the elasticity of substitution, and η_D is the own-price elasticity of industry output demand; L is the quantity of labor demand, w is the wage rate, and Y is output.

The first term in the total labor demand elasticity expression can be interpreted as the constant-output labor demand elasticity, or the "substitution effect." As the price of labor rises, firms substitute away from labor in favor of other inputs. The substitution effect captures this adjustment on the part of profit maximizing firms. The higher the substitutability of labor with respect to other factors of production, the larger is the constant-output labor demand elasticity. The second term in the expression captures the "scale effect." As the cost of hiring labor rises, output price increases, which in turn lowers industry output demand, and hence lowers labor demand. The total labor demand elasticity can be viewed as the weighted average of the constant-output labor demand elasticity and the own-price output demand elasticity.

As Hamermesh (1993) points out, the choice of output (Y) will determine whether we are estimating the total labor demand elasticity, or the constant output labor demand elasticity. If the measure of output embodies the overall industry demand conditions, then we will be estimating the total labor demand elasticity.

We specify in Equation (7) a canonical labor demand function found in Hamermesh (1993); where industry, county, and year are denoted by i, c, t, respectively.

$$\ln(L_{ict}) = \beta_0 + \beta_{1i} \ln(w_{ict}) + \beta_{2i} \ln(Y_{ict}) + \beta_{3i} t + \vartheta_{ic} + \varepsilon_{ict}. \tag{7}$$

In Equation (7), L denotes employment, w the real wage rate, and Y real output, ϑ is a time invariant industry-county fixed effects, and ε is idiosyncratic error. In the above specification β_{1i} gives the industry specific total labor demand elasticity while the term $\beta_{3i}t$ allows the intercept in the labor demand function to vary across years.

For identification of the parameters in Equation (7) we rely on the strict exogeneity assumption (Wooldridge, 2010): $E(\varepsilon_{ict}|x_{ic1}, \ldots, x_{icT}, \vartheta_{ic}) = 0, t = 1, 2, \ldots, T$; where x denotes the vector of explanatory variables in the labor demand function. The strict exogeneity assumption implies that ε_{ict} is uncorrelated with all past and future values of the explanatory variables as well as the industry-county fixed effect. However, this assumption still allows for arbitrary correlations between the explanatory variables and the industry-county fixed effects; which means that we cannot estimate Equation (7) using OLS since the explanatory variables could be endogenous in the equation. First-differencing Equation (7), however, eliminates the industry-county fixed effects and yields Equation (8) which can be estimated using OLS. Note that the time trend in Equation (7) leaves an intercept in Equation (8). In Table 3 we present the OLS estimation results.

$$\Delta \ln(L_{ict}) = \beta_{1i} \Delta \ln(w_{ict}) + \beta_{2i} \Delta \ln(Y_{ict}) + \beta_{3i} + \Delta\varepsilon_{ict}. \tag{8}$$

In economic terms, the strict exogeneity assumption implies that labor supply is perfectly elastic at the industry-county level. This assumption is maintained in most studies which estimate labor demand elasticity—Slaughter (2001) and Hasan et al. (2007) are two prominent examples; Lichter et al. (2014) provide a complete list of studies that use this identifying assumption. We use two empirical facts to justify our identifying assumption. First, the use of county as the geographical unit: Internal Revenue Service data shows that in the period 1980–2000 about 5–6 percent of the U.S. population moved across county borders per year and that this migration is sufficiently large to affect local labor market outcomes (Molloy, Smith, and Abigail, 2011). Second, in addition to migrants from outside the local labor market, empirical evidence also points to local residents significantly increasing their labor force participation following a localized labor shock (Bartik 1991, 2001; Eberts and Stone, 1992).[14]

The strict exogeneity assumption can be violated if Y and ε are correlated. In our case this is possible because of measurement error: we do not observe industry-county output but impute it from output at the industry-state level and/or due to simultaneity: employment might drive output, although this is less likely. To solve this possible endogeneity problem we estimate Equation (8) using the control function (CF) approach (Train, 2009;

[14] A referee points out that labor supply may not be perfectly elastic in the short-run (Bartik, 1993; Partridge and Rickman, 2003, 2006; Rowthorn and Glyn, 2006) and analogous to labor demand elasticity might vary across regions (Greenwood and Hunt, 1984; Partridge and Rickman, 1997). Our contention is that by focusing on a very small geography like a county, we mitigate some of these concerns, in that following a shock to local labor demand, wages might adjust very rapidly across a cluster of adjacent counties as workers can move quickly over smaller distances in the short-run, while wages take more time to adjust over a broader geography like states as migrating over larger distances is more expensive. This mechanism is not possible in studies where the geographical unit of observation is a state or country. In such cases wage adjustment should take longer time.

TABLE 3: Estimates of Wage Elasticity of Labor Demand

Industry	$N \times T$		Model	Estimation	β_1	β_{1i}	γ_i	β_2	R^2	Log-Likelihood	$\sqrt{\sigma^2_{\varepsilon i}}$
Construction	61,018	(1)	Constant parameter	OLS	-0.01^{***} (0.004)	–	–	0.92^{***} (0.004)	0.90	–	0.07
		(2)		OLS+CF	-0.14^{***} (0.01)	–	–	0.48^{***} (0.01)	0.71	–	0.12
		(3)	Random parameter	MSL	0.02 [0.07]	-4.75^{***} (0.15)	0.39^{***} (0.04)	0.84^{***} (0.002)	–	46,717	0.05
		(4)		MSL+CF	0.15 [0.13]	-2.17^{***} (0.04)	-0.51^{***} (0.03)	0.48^{***} (0.01)	–	76,668	0.06
Finance/insurance/ real-estate/service	66,321	(1)	Constant parameter	OLS	-0.03^{***} (0.005)	–	–	0.93^{***} (0.006)	0.92	–	0.06
		(2)		OLS+CF	-0.02 (0.03)	–	–	0.18^{***} (0.02)	0.33	–	0.20
		(3)	Random parameter	MSL	0.10 [1.35]	-4.76^{***} (0.14)	0.81^{***} (0.02)	0.90^{***} (0.001)	–	65,100	0.04
		(4)		MSL+CF	0.005 [0.05]	-7.4^{***} (0.02)	1.49^{***} (0.002)	0.20^{***} (0.007)	–	98,217	0.04
Manufacturing	56,627	(1)	Constant parameter	OLS	-0.07^{***} (0.01)	–	–	0.78^{***} (0.01)	0.74	–	0.10
		(2)		OLS+CF	-0.24^{***} (0.03)	–	–	0.05 (0.04)	0.12	–	0.19
		(3)	Random parameter	MSL	0.11 [1.85]	-4.90^{***} (0.10)	0.85^{***} (0.01)	0.69^{***} (0.002)	–	29,840	0.07
		(4)		MSL+CF	0.21 [0.38]	-2.28^{***} (0.05)	0.37^{***}	-0.02 (0.02)	–	49,887	0.09
Retail trade	66,636	(1)	Constant parameter	OLS	-0.05^{***} (0.01)	–	–	0.80^{***} (0.01)	0.78	–	0.07
		(2)		OLS+CF	-0.17^{***} (0.04)	–	–	0.12^{***} (0.01)	0.22	–	0.14
		(3)	Random parameter	MSL	0.08 [0.38]	-3.95^{***} (0.12)	0.55^{***} (0.02)	0.68^{***} (0.002)	–	55,136	0.05
		(4)		MSL+CF	0.09 [0.25]	-3.47^{***} (0.03)	0.77^{***} (0.005)	0.13^{***} (0.005)	–	95,876	0.05

Notes: N = number of counties; T = number of years. In constant parameter regression estimations dependent variable is $\Delta\log(L_{ict})$. Clustered standard error in parenthesis; cluster ID is BEA economic zone. $\bar{\beta}_1 = \exp[\beta_1 + 0.5\exp(\gamma)^2]$ is mean of log normal distribution. $\sqrt{\sigma^2_{\beta_1}} = \exp[\exp(\gamma)^2 - 1]\exp[2\beta_1 + \exp(\gamma)^2]$ is standard deviation of log normal distribution. Significance level: $^{***}P < 0.001$. CF, control function; MSL, maximum simulated likelihood.

Petrin and Train, 2010; Wooldridge, 2014) the results of which are again presented in Table 3.

$$\begin{aligned}\Delta \ln (Y_{ict}) = \delta_{0i} + \delta_{1i} \Delta \ln (w_{ict}) + \delta_{2i} Bartik_{IVct} + \delta_{3i} lat_i mil_{s(c)t} + \delta_{4i} lon_i mil_{s(c)t} \\ + \delta_{5i} \log (PPI_t) + \delta_{6i} \log (PPI_{t-1}) + \delta_{7i} \log (PPI_{t-2}) + \eta_{ict}.\end{aligned} \tag{9}$$

To operationalize the CF approach we first postulate Equation (9) which shows the change in output as a function of several exogenous variables. In Equation (9), *lat* and *lon* refer to county latitude and longitude, respectively, *mil* is the dollar value of federal military contracts received by the state in which the county is located. The military contract variable is available at the year-state level, so for it to have differential effects on counties located in the same state we interact it with county latitude and longitude. The producer price index and its lags are included because an industry-county is a very small player in a highly integrated world economy and therefore is analogous to a perfectly competitive firm whose profit maximizing output is determined by the market price level. Bartik's IV predicts the output growth of a county-industry but is not affected by it as explained in the data section.

In the CF approach, we assume that the idiosyncratic errors $\Delta\varepsilon_{ict}$ and η_{ict} are correlated, and this correlation is in fact the reason behind the endogeneity problem. In our particular application we assume that this correlation takes a simple form[15] as given in Equation (10),

$$\Delta\varepsilon_{ict} = \lambda\eta_{ict} + \mu_{ict}. \tag{10}$$

The CF estimator then involves a two-stage estimation procedure.

Stage 1: Run a regression based on Equation (9) and compute the residuals. Let the residual be denoted by $\hat{\eta}_{ict}$.

Stage 2: Run regression based on Equation (8) with $\hat{\eta}_{ict}$ as an additional explanatory variable.

The resulting estimator is the CF estimator and it provides consistent estimates of the parameters in Equation (7). This particular CF estimator is equivalent to a 2SLS estimator (Hausman, 1978).

In the labor demand equation presented above the coefficients, the coefficient of log wage is a constant: there is no variation in the wage elasticity of labor demand across counties and/or over time. In the constant parameter linear panel data framework discussed earlier we cannot estimate a β_{1i} for each county-year combination, otherwise, the number of parameters to estimate will be greater than the number of observations in the data. To incorporate regional variation in labor demand elasticity, we can estimate a β_{1i} for each county. The problem with this approach is that there is no guarantee that all the β_{1i} will have the correct sign and the sample sizes will be significantly smaller making the estimates unreliable.

An alternative approach to incorporate spatial heterogeneity in labor demand elasticity would be to interact log wage with some variable which we believe affects labor demand elasticity and which itself varies across counties. However, there are two drawbacks with this approach. One, since multiple factors influence labor demand elasticity, the result will crucially depend on the choice of the interaction variables. Two, theory provides little guidance as to what these interaction variables should be.

Borrowing from ideas in the random parameter discrete choice literature (Train, 2009) we use a more robust approach to incorporate spatial heterogeneity in labor demand

[15] Other correlation structures could be specified. We choose the simplest structure for computational ease and also since this way we can relate the results of the constant and random parameter models.

elasticity: we assume that the parameter β_{1i} is a random variable.[16] In which case we cannot estimate β_{1i}, but we can estimate the parameters which describe the distribution of β_{1i} in the population of counties. In this paper, we assume for simplicity that β_{1i} varies over counties, but not over time. Equation (11) is a modified version of Equation (7) and includes β_{1ic} to model spatial heterogeneity in labor demand elasticity.

$$\ln(L_{ict}) = \beta_{0i} + \beta_{1ic}\ln(w_{ict}) + \beta_{2i}\ln(Y_{ict}) + \beta_{3i}t + \vartheta_{ic} + \varepsilon_{ict}. \quad (11)$$

Again, first differencing removes the county fixed effects and yields our estimation equation in (12),

$$\Delta\ln(L_{ict}) = \beta_{1ic}\Delta\ln(w_{ict}) + \beta_{2i}\Delta\ln(Y_{ict}) + \beta_{3i} + \Delta\varepsilon_{ict}. \quad (12)$$

To estimate Equation (12), we use Maximum Simulated Likelihood (MSL) which requires us to specify a parametric probability distribution for β_{1ic} and $\Delta\varepsilon_{ict}$. We assume that $\Delta\varepsilon_{ict}$ is normal with mean zero and variance $\sigma^2_{\varepsilon_i}$.

For labor demand elasticity we assume that it is distributed i.i.d. $\ln N(\beta_{1i}, \exp(\gamma_i))$ in the population of counties, where β_{1i} and $\exp(\gamma_i)$ are the mean and variance of β_{1ic}'s natural logarithm. The log normal distribution[17] assures that β_{1ic} is always positive while $\exp(\gamma_i)$ guarantees a positive value for the shape parameter of the lognormal distribution. The mean and variance of β_{1ic} are then given by the following formulas:

$$\bar{\beta}_{1i} = E[\beta_{1ic}] = \exp\left[\beta_{1i} + \frac{\exp(\gamma_i)}{2}\right], \quad (13)$$

$$\sigma^2_{\beta_{1i}} = \text{Var}(\beta_{1ic}) = \left[\exp(\exp(\gamma_i)) - 1\right]\exp\left[2\beta_{1i} + \exp(\gamma_i)\right]. \quad (14)$$

We first estimate the random parameter model assuming that the strict exogeneity assumption is valid. In this case estimation involves maximizing the log-likelihood function in (15) with respect to the vector $(\beta_{1i}, \gamma_i, \beta_{2i}, \beta_{3i}, \sigma^2_{\varepsilon_i})$ where, $\emptyset$ and $\emptyset_{\ln}$ denote the normal and lognormal probability density functions respectively.

$$\ln LL = \sum_c \sum_t \log\left[\int_0^\infty \emptyset(\Delta\varepsilon_{ict}(\beta_{1ic}))\,\emptyset_{\ln}(\beta_{1ic})\,d\beta_{1ic}\right]. \quad (15)$$

The integral in (15) cannot be computed analytically and therefore the log-likelihood function is evaluated by simulation. The simulation is performed as follows. Given $(\beta_{1i}, \gamma_i, \beta_{2i}, \beta_{3i}, \sigma^2_{\varepsilon_i})$, we draw value for β_{1ic} from the lognormal density $\emptyset_{\ln}$. The draws are independent across counties but same within counties and over time. We then compute the normal density $\emptyset_{ict}$ for that draw. We repeat this process R times and find the average value of $\emptyset_{ict}$. The simulated log-likelihood function is given in (16), where r indexes a draw from the log-normal distribution.

$$\text{Log } SLL(\theta_i) = \sum_c \sum_t \left(\frac{1}{R}\sum_r \emptyset_{ictr}\right). \quad (16)$$

We use the "Nelder-Mead" algorithm and $R = 100$ to find the maximum value of the simulated log-likelihood function which then yields the parameter estimates shown in

[16]See Hsiao and Pesaran (2004) for other approaches in specification and estimation of random parameter panel data models.

[17]As Train (2009) mentions, economic theory rarely provides any guide on the distribution of economic parameters. In a parametric setting, the researcher must choose from a family of distribution and the lognormal distribution is most often the first choice of researchers.

Table 3 under the MSL (Maximum Simulated Likelihood) model. The "Nelder-Mead" technique is a search algorithm which does not require computations of derivatives and is therefore faster than the gradient based numeric optimization procedures. We also estimate the random parameter model using the CF approach. In the CF approach we just add the regression residual $\hat{\eta}_{ict}$ in Equation (12) and then estimate the parameters using MSL. The CF results are also presented in Table 3 under the MSL+CF category.

We discuss in detail the estimation results alluded earlier. For brevity, we restrict our attention to the estimates of wage elasticity of labor demand since they are the primary focus of this paper.

In the construction sector, the OLS+CF[18] estimate of the average value of labor demand elasticity is 0.14, which is marginally lower compared to the MSL+CF estimate of 0.15. These estimates are, however, significantly higher than the plain OLS and MSL estimates of 0.01 and 0.02: controlling for the endogeneity of output raises labor demand elasticity. We also find that in the construction sector, the MSL+CF approach increases the spatial variation in labor demand elasticity in that the standard deviation of the lognormal distribution goes up to 0.13, from 0.07, the standard deviation of the lognormal distribution under the simple MSL approach.

The MSL+CF approach yields an estimate of 0.005 for the average value of labor demand elasticity in the finance/insurance/real-estate/service industry. This value is somewhat closer to the OLS and CF estimates of 0.03 and 0.02, respectively, but significantly lower than the MSL estimate of 0.10. The MSL estimates also point to significant heterogeneity in labor demand elasticity with a standard deviation of 1.35 for the lognormal distribution, which falls significantly to 0.05 when the MSL+CF approach is used. The wide discrepancy in the MSL and MSL+CF estimates for this sector might be explained by two facts. First, the finance/insurance/real-estate/service industry is a large sector formed by combining a variety of subindustries. Second, and more importantly, this industry passed through two major bubbles (dot-com and subprime mortgage) and then crashes during the period of his study.

The OLS and CF estimates of labor demand elasticity in the manufacturing sector are 0.07 and 0.24, respectively. The MSL and MSL+CF estimates on the other hand are 0.11 and 0.21, respectively. Like in the finance/insurance/real-estate/service industry, the MSL+CF approach reduces the spatial heterogeneity of labor demand elasticity by lowering the standard deviation of the lognormal distribution to 0.38 from 1.85 under simple MSL.

A similar picture emerges in the retail trade industry where the OLS and CF estimates are 0.05 and 0.17, respectively, while they are 0.08 and 0.09 under the MSL and MSL+CF approaches, respectively. As before, the MSL+CF approach produces less spatial heterogeneity in labor demand elasticity, than the simple MSL: the standard deviation of the lognormal distribution falls from 0.38 to 0.25.

We can summarize the results below:

(1) Except the finance/insurance/real-estate/service industry, in all other industries, controlling for the endogeneity of output raises the elasticity estimates. This hold for both constant and random parameter models.

(2) For all industries, when we do not control for the endogeneity of output, the estimates rises with randomization of the elasticity parameter. The exact opposite is true

[18]OLS+CF refers to the two-step approach where step 1 is the running the CF regression and step 2 is running the OLS regression with the CF residual as an additional variable. MSL+CF also refers to a two-step approach—here the second step involves running the Maximum Simulated Likelihood.

when endogeneity of output is controlled: the estimates fall with randomization of the elasticity parameter.[19]

(3) In the random parameter model the CF approach estimates less spatial heterogeneity in labor demand elasticity as compared to the simple MSL approach. This result, however, does not hold for the construction sector.

Before we move on, it is important to mention briefly the results (Appendix B) of the first-stage regression in the CF approach. We find that all the regressions are highly significant, as pointed out by the very high values of the F-statistics, plus, most of the coefficients in the regression are also individually highly statistically significant.[20] Exceptions are the military contract variables which are not significant in the finance/insurance/real-estate/service and retail trade industries. This is expected as most of the benefits of such contract likely fall on the other two sectors: construction and manufacturing, for which they are highly statistically significant.

4. REGIONAL VARIATIONS IN LABOR DEMAND ELASTICITY AND ITS DETERMINANTS

In the previous section we presented estimates for the mean and standard deviation of the lognormal distributions which describe the spatial variations in labor demand elasticity for four industries in the U.S. These distributions then allows us to calculate average labor demand elasticity for each industry-county (see Appendix C)—in Figure 4 we map the weighted averages of the four industry-county elasticity using industry-county employment shares as weights. In this section we attempt to relate these variations in labor demand elasticity to differences in other county characteristics. This analysis will reveal if the variations in labor demand elasticity is random or is systematically related to other county characteristics. All analysis from now on is based on labor demand elasticity estimates calculated using the MSL+CF method.

In Table 4 we present regression results which show some clear trends in the spatial variations in labor demand elasticity. We find that counties with higher levels of natural amenity have higher labor demand elasticity. Industry-county competition has a negative relationship with labor demand elasticity. Industry-county specialization also has a negative relationship, as long as we control for industry-county competition, otherwise it has a statistically insignificant positive relationship. The level of urbanization as measured by the dummy variables has a positive relationship with labor demand elasticity: more urbanized counties have higher labor demand elasticity. Finally, counties with right-to-work laws have lower labor demand elasticity—this relationship is not statistically significant. This result, however, goes contrary to economic sense which says that right-to-work laws should make firms more flexible to hire/fire workers and therefore push up labor demand elasticity. Given that a lot of government policies are at play at the county level, we need a more sophisticated approach to elicit the relationship between the right-to-work law and labor demand elasticity (Holmes, 1998). Below we describe just such an approach.

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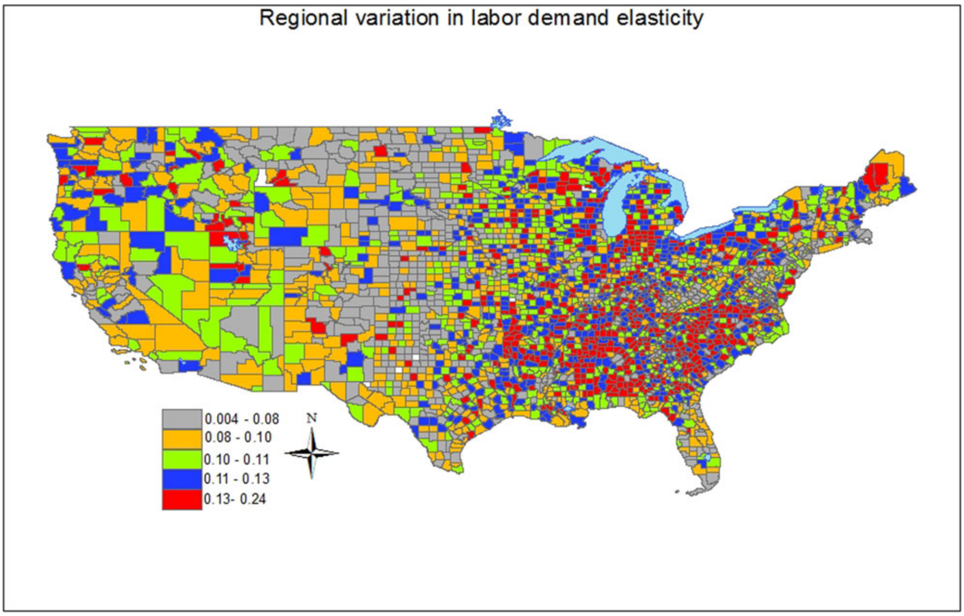
[19]Revelt and Train (1998) report higher estimates of mean values of coefficients in a random parameter model as compared to a constant parameter model. They argue that in a constant parameter model the heterogeneity in the coefficient is captured by the error term which lowers the estimate of the coefficient, unlike a random parameter model, where the heterogeneity in the coefficients is explicitly modeled and not attributed to the error term. In the constant parameter CF approach it is possible that the heterogeneity in the coefficient is captured by the term $\hat{\eta}_{ict}$ and not the error term which explains why explicitly modeling parameter heterogeneity does not increase the mean estimate of labor demand elasticity under MSL+CF.

[20]This result alleviates concerns of weak instruments (Stock and Yogo, 2005).



Notes: The above graph shows the weighted average industry-county own wage labor demand elasticity for counties in the conterminous U.S. The industries included in the average are: construction, finance/insurance/real-estate/service, manufacturing, and retail trade. The weights are constructed using the average industry-county employments in the period 1988–2010.

FIGURE 4: Regional Variations in Labor Demand Elasticity.

TABLE 4: Factors Affecting County Labor Demand Elasticity

Variable	(1)	(2)	(3)	(4)
Natural amenity scale	0.00008	0.0005**	0.0005**	0.0005**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Industry-county specialization	−0.0009*	−0.0007	0.0002	–
	(0.0004)	(0.0004)	(0.0004)	
Industry-county competition	−0.001***	−0.001**	–	−0.001**
	(0.0003)	(0.0004)		(0.0003)
Nonmetro counties: urban	−0.002***	−0.002***	−0.002***	−0.002***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Nonmetro counties: rural	−0.008***	−0.007***	−0.009***	−0.008***
	(0.0008)	(0.0008)	(0.0006)	(0.0007)
Right-to-work law	−0.0006	–	–	–
	(0.0005)			
Industry fixed effects	Yes	Yes	Yes	Yes
State fixed effects	No	Yes	Yes	Yes
Number of observations	12,092	12,092	12,092	12,092
R^2	0.91	0.91	0.91	0.91

Notes: Unit of observation is industry-county. Dependent variable is the absolute value of labor demand elasticity. Cluster robust standard error in parenthesis. Cluster ID is BEA economic zone. Significance levels: $*P < 0.05$, $**P < 0.01$, $***P < 0.001$.

What explains the relationships in Table 4? One interpretation is that some of the relationships in Table 4 captures the biases in our elasticity estimates because of our assumption of perfectly elastic labor supply. For example, a county with higher level of natural amenity might have a better chance of attracting workers than a comparable county with lower natural amenity level, thereby implying different supply elasticity for the two counties. Similarly, metropolitan and urban counties might be able to attract more workers given that they offer better consumption opportunities to its inhabitants than rural counties. However, given the very small magnitudes of the effects in Table 4, we can be reasonably confident that the biases—if they exist—are very small.

The effect of industry-specialization and industry-competition on labor demand elasticity is more difficult to explain since economic theory does not provide any guide as to what these relationships should be. One possible explanation for industry-county competition is that more firms in an industry increases firms' search and matching costs of hiring/firing workers and so they become less responsive to wage shocks. The effect of industry-county specialization is more ambiguous and difficult to explain.

To find the effect of probusiness policies on labor demand elasticity we follow the research design laid out in Holmes (1998): we look for abrupt changes in labor demand elasticity at borders which divide states with and without right-to-work laws. At state borders factors that affect labor demand elasticity are approximately same on both sides of the border and so the difference in labor demand elasticity on two sides can only be attributed to government policy. Equation (17) describes the regression equation that is used to test this hypothesis,

$$\check{\beta}_{1ic} = \theta_{rc} + \alpha\,(x_c) + \delta y_c + \varepsilon_{ic}. \tag{17}$$

In Equation (17), θ_{rc} is a shift parameter which equals θ if the county belongs to a right-to-work state, zero otherwise. Following Holmes (1998) we consider two border segments.[21] Segment 1 begins at the western end of the Oklahoma-Texas border and ends where the Maryland-Virginia border meets the Atlantic Ocean. Segment 2 begins where the Minnesota-North Dakota border intersects the boundary with Canada and it ends at the western end of the Oklahoma-Kansas border. Segment 1 is 2,386 miles long while segment 2 has a length of 1,891 miles. The variable x_c is used to mark points every 1 mile along these two-border segments. For example, $x_c = 0$ and $x_c = 2,386$ are at the start and end of border segment 1 respectively. In Equation (17), x_c is the mile marker closest to the centroid of the county polygon and y_c measures the distance between them—y_c is negative if the county is in a right-to-work state and positive otherwise. $\alpha(x_c)$ represents a general continuous function of x_c. Following Holmes (1998) we restrict ourselves to counties within 100 miles of the two border segment. Holmes (1998) justifies a nonlinear relationship between the dependent variable and x_c since movement along x covers a large distance while movement along y is small—100 miles on each side of the border, and so a linear relationship between the dependent variable and y is reasonable.

In Table 5, we show the OLS estimates of θ_{rc} for two different specifications. In both specifications we use a fourth-degree polynomial to approximate $\alpha(x_c)$. In specification 1, δ is same for both border segments while in specification 2 they are different. The positive estimate of θ under both specifications supports our hypothesis that labor demand elasticity is higher in states with right-to-work laws or more precisely states which are more probusiness.[22]

[21]See Holmes (1998) for the map which outlines the two border segments.

[22]As a robustness check we re-estimated the parameters in Equation (17) after assigning Texas, Oklahoma, Michigan, and Indiana as *non-right-to-work* states, since in these states the laws were

TABLE 5: The Effect of Right-to-Work Law on Labor Demand Elasticity

Variable	(1)	(2)
θ_{rc}	0.08***	0.08***
	(0.005)	(0.005)
y_c	0.0005***	–
	(0.00004)	
$y_{c,ns}$	–	0.0002***
		(0.00007)
$y_{c,ew}$	–	0.0006***
		(0.00005)
Number of observations	972	972

Notes: Dependent variable is absolute value of labor demand elasticity. θ_{rc} is a dummy variable which takes a value of one if county is in a right-to-work state, zero otherwise. The variable y measures the distance between the county centroid and nearest mile-marker; y is negative for counties in right-to-work state, positive otherwise. Cluster robust standard error in parenthesis. Clustering ID is BEA economic zone. Significance level: $^{***}P < 0.001$.

5. CONCLUSION

In this study we find evidence of spatial variations in labor demand elasticity and provide point estimates for them at the industry-county level. We also find that the spatial variations in elasticity are not the result of some random assignment but are systematically related to certain spatial features of the U.S. economy and urban landscape. In this section, we discuss some future research ideas that could extend and improve this study.

One obvious extension of this study will be to relax the assumption of perfectly elastic labor supply. This can be done either by finding a reliable instrument for wage or by explicitly modeling labor supply and taking the simultaneous equations estimation approach. In the latter approach labor supply can emerge from workers metropolitan residence location choice, which can be modeled using random utility models. Such an approach will also allow the joint estimation of the labor and land/housing markets since labor supply and housing demand are two sides of the same coin, at least at a metropolitan area level. Another direction of research should be to explore the theoretical underpinnings of the relationships between labor demand elasticity and county characteristics, especially industry-county specialization and industry-county competition. This will improve our understanding of the dynamics of local labor markets and how they are related to the spatial organization of economic activity and urban structure.

APPENDIX A: 1993 RURAL–URBAN CONTINUUM CODE (ALSO KNOWN AS THE "BEALE CODE")

Metro counties

0 Central counties of metro areas of 1 million population or more

1 Fringe counties of metro areas of 1 million population or more

2 Counties in metro areas of 250,000 to 1 million population

3 Counties in metro areas of fewer than 250,000 population

implemented either during or after our study period. This reassignment does not change the results reported in Table 5 significantly.

Nonmetro counties

4 Urban population of 20,000 or more, adjacent to a metro area
5 Urban population of 20,000 or more, not adjacent to a metro area
6 Urban population of 2,500–19,999, adjacent to a metro area
7 Urban population of 2,500–19,999, not adjacent to a metro area
8 Completely rural or fewer than 2,500 urban population, adjacent to a metro area
9 Completely rural or fewer than 2,500 urban population, not adjacent to a metro area

Population in 1990. Source: http://www.ers.usda.gov/briefing/rurality/ruralurbcon/.

APPENDIX B: CONTROL FUNCTION FIRST-STAGE REGRESSION RESULTS

Variable	Construction	Finance/insurance/ real-estate/service/	Manufacturing	Retail trade
$\Delta\ln(w_{ict})$	-0.29^{***}	-0.02	-0.23^{***}	-0.20^{***}
	(0.02)	(0.03)	(0.02)	(0.04)
$Bartik's\ IV_{ct}$	0.68^{***}	0.68^{***}	0.36^{***}	0.92^{***}
	(0.07)	(0.05)	(0.06)	(0.04)
$lat_c mil_{s(c)t}$	-0.0003^{***}	0.00002	-0.0001^{***}	-0.00001
	(0.00002)	(0.00002)	(0.00003)	(0.00001)
$lon_c mil_{s(c)t}$	-0.00007^{***}	-0.000005	-0.00007^{***}	-0.000009
	(0.00001)	(0.000009)	(0.00001)	(0.000006)
$\text{Log}(PPI_t)$	-0.62^{***}	-0.95^{***}	-0.56^{***}	-1.21^{***}
	(0.04)	(0.03)	(0.05)	(0.02)
$\text{Log}(PPI_{t-1})$	0.73^{***}	1.04^{***}	0.26^{***}	1.07^{***}
	(0.05)	(0.04)	(0.06)	(0.03)
$\text{Log}(PPI_{t-2})$	-0.28^{***}	-0.14^{***}	0.26^{***}	0.12^{***}
	(0.03)	(0.03)	(0.05)	(0.02)
$N \times T$	61018	66321	56627	66636
R^2	0.08	0.03	0.03	0.12
F-statistic	815	320	310	1309

Notes: Unit of observation is industry-county-year. N, number of counties; T, number of years. Dependent variable is one-year change in log of real industry-county output ($\Delta\ln(Y_{ict})$). w = real wage, $Bartik's\ IV_{ct} = \frac{\sum_i Employees_{ict}[\ln(Y_{i(-c)t}) - \ln(Y_{i(-c)t-1})]}{\sum_i Employees_{ict}}$, lat = county latitude, lon = county longitude, mil = federal military contract received by a state, PPI = national producer price index. Clustered standard error in parenthesis. Cluster ID is BEA economic zone. Significance codes: ***P < 0.01.

APPENDIX C: COMPUTING COUNTY SPECIFIC LABOR DEMAND ELASTICITY

In this Appendix we describe step-by-step how to calculate county specific labor demand elasticity based on the estimates from the random parameter panel data model. The procedure below is taken from Train (2009).

Consider Equation (A.1),

$$\hat{\phi}_{\ln}(\beta_{1ic}|\Delta\varepsilon_{ict}) \times f(\Delta\varepsilon_{ict}) = \phi(\Delta\varepsilon_{ict}|\beta_{1ic}) \times \phi_{\ln}(\beta_{1ic}), \tag{A.1}$$

which states that the joint density of β_{1ic} and $\Delta\varepsilon_{ict}$ can be written as the product of the probability of $\Delta\varepsilon_{ict}$ and the probability of β_{1ic} conditional on $\Delta\varepsilon_{ict}$ (left-hand side), or with the other direction of conditioning, as the product of the probability of β_{1ic} and the probability of $\Delta\varepsilon_{ict}$ conditional on β_{1ic} (right-hand side).

Rearranging Equation (A.2) we get,

$$\hat{\phi}_{\ln}(\beta_{1ic}|\Delta\varepsilon_{ict}) = \frac{\phi(\Delta\varepsilon_{ict}|\beta_{1ic}) \times \phi_{\ln}(\beta_{1ic})}{f(\Delta\varepsilon_{ict})}. \tag{A.2}$$

Note that the conditional probability of β_{1ic} will vary over the years because $\Delta\varepsilon_{ict}$ changes from year to year. This implies that we can get $\bar{\beta}_{1ict}$, the average labor demand elasticity for industry i located in county c at year t, using Equation (A.3),

$$\bar{\beta}_{1ict} = \int \beta_{1ic}\hat{\phi}_{\ln}(\beta_{1ic}|\Delta\varepsilon_{ict})\,d\beta_{1ic}, \tag{A.3}$$

which can be rewritten as

$$\bar{\beta}_{1ict} = \int \beta_{1ic}\frac{\phi(\Delta\varepsilon_{ict}|\beta_{1ic}) \times \phi_{\ln}(\beta_{1ic})}{f(\Delta\varepsilon_{ict})}d\beta_{1ic}. \tag{A.4}$$

The simulated counterpart of $\bar{\beta}_{1ict}$ is $\check{\beta}_{1ict}$ which is described by the formula below:

$$\check{\beta}_{1ict} = \sum_r w^r \beta_{1ic}^r, \tag{A.5}$$

where

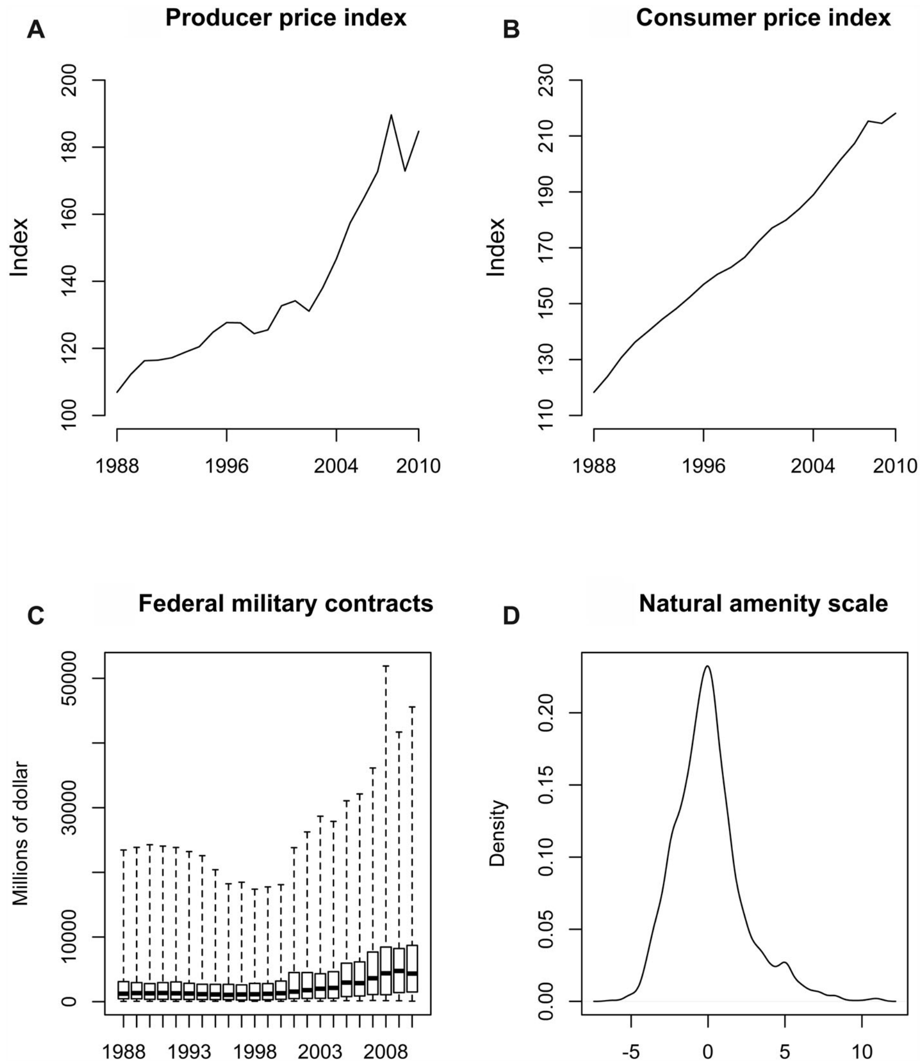
$$w^r = \frac{\phi\left(\Delta\varepsilon_{ict}|\beta_{1ic}^r\right)}{\sum_r \phi\left(\Delta\varepsilon_{ict}|\beta_{1ic}^r\right)}. \tag{A.6}$$

Since we assume time invariant labor demand elasticity, we modify Equations (A.5) and (A.6) to get $\check{\beta}_{1ic}$.

$$\check{\beta}_{1ic} = \sum_r w^{r\prime} \beta_{1ic}^r, \tag{A.7}$$

$$w^{r'} = \frac{\phi\left(\Delta\varepsilon_{ict}|\beta_{1ic}^r\right)}{\sum_t \sum_r \phi\left(\Delta\varepsilon_{ict}|\beta_{1ic}^r\right)}. \tag{A.8}$$

APPENDIX D: SOME ADDITIONAL PLOTS



Notes: Producer and Consumer price index data are from the Bureau of Labor Statistics. Military contracts data is from U.S. Census Bureau. Natural amenity scale data is from United States Department of Agriculture.

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