Regional variations in Labor Demand Elasticities: evidence from U.S. Counties

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Regional Variations in Labor Demand Elasticities: Evidence from U.S. Counties*

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Abstract

We use a large panel dataset covering the years 1988 to 2010 to estimate county specific total wage elasticities of labor demand for four highly aggregated industries in the United States. Our industries are construction, finance/real estate/service, manufacturing, and retail trade, which together employ on average over eighty percent of the U.S. national labor force per year. We use both the conventional constant coefficient panel data model and a random coefficients panel data model to estimate labor demand elasticities in various industries. We find the labor demand curves in all the industries studied to be downward sloping. We also find significant evidence that the total wage elasticity of labor demand exhibits regional variation. The labor demand estimates obtained in this study are useful to investigate the differential impact of various shocks and policy changes on the labor market. As an example, we use the estimated

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county specific labor demand elasticities to identify the impact of union membership and right to work laws on labor demand. We show that labor demand tends to become less elastic with higher union membership rates. We also find that labor demand becomes more elastic if a right to work law is in place.

Keywords: Labor Demand Elasticity, Random Parameter Model, Union Membership, Right to Work Law

JEL classification: C35, J20, J23, R14, R15, R21, R41

1 Introduction

The estimation of wage elasticities of labor demand has attracted significant attention in empirical labor economics. Hamermesh (1993) provides an exhaustive review of the early research that has been done in this area. According to Hamermesh (1993), the absolute value of the constant-output wage elasticity of labor demand for homogeneous labor in the U.S. is between 0.15 and 0.75, with 0.30 being an approximate mean; the absolute value of the estimates for the total wage elasticity of labor demand vary between 0.12 and 1.92. Homogeneous labor implies that we cannot distinguish workers based on their skill level.

Fuchs et al. (1998) survey sixty five labor economists and confirm Hamermesh's findings. They report mean absolute values for constant-output and total wage elasticity of labor demand equal to 0.42 and 0.63, respectively. More recently, Slaughter (2001), using the NBER productivity database, estimates absolute values of the total wage elasticity of labor demand for the manufacturing sector in the U.S. in the range of 0.24 to 0.70. Hasan et al. (2007), using small industry panel data, estimate the absolute value of the total wage elasticity of labor demand in India's manufacturing sector to be around 0.40. In Table 1 we provide a list of studies that estimate total wage elasticities of labor demand from a variety of different data sets.

Most studies cited in Table 1 estimate wage elasticities of labor demand for one sector or industry, in particular the manufacturing sector, and assume no regional variation in the wage elasticity of labor demand. While regional variation in the labor demand elasticity may be safely neglected for smaller countries such as New Zealand, for a large country, such as the United States, this may not be a reasonable assumption. In the U.S., for example, history, geography, and politics vary considerably across counties, and all these factors are likely to induce regional variation in the wage elasticity of labor demand. Using the County Business Patterns (CBP), we address the issues of regional and industry heterogeneity for labor demand estimates. In particular, we estimate county specific labor demand elasticities for multiple industries located in the U.S. This makes our study unique in the empirical labor demand literature.

Our use of a single data source makes comparing elasticities across industries easier than comparing elasticities from different studies that vary in methodology and data. Our elasticity estimates can therefore be used to calibrate local labor markets that may be part of larger regional economic models. These models can be used, for example, to study how external shocks might have asymmetric effects on different local labor markets based in part on variations in their labor demand elasticities.

To obtain county specific total wage elasticities of labor demand we follow a two-step procedure. In step-one, we specify a canonical log linear labor demand function. Then we use the traditional first-difference panel data estimator to get the following estimates for the absolute values of industry specific total wage elasticities of labor demand: 0.32 for construction, 0.11 for finance-insurance-real estate-service, 0.23

for manufacturing, and 0.23 for retail. Our industry specific total labor demand elasticities fall within the range mentioned in Hamermesh (1993).

In step-two, we assume that the total wage elasticity of labor demand for an industry is not a constant but a random variable, distributed log-normally in the population of counties with unknown parameters. The log-normal distribution ensures that the absolute value of the labor demand elasticity is always positive. We then estimate the parameters of the log normal distribution by the method of maximum simulated likelihood.

The means and standard deviations of the log-normal distribution for the four industries are as follows: (0.08, 0.01) for construction, (0.34, 3.26) for finance-insurance-real estate-service, (0.38, 3.97) for manufacturing, and (0.35, 0.98) for retail trade. For all four industries, the variance parameter is statistically significant, which suggests the presence of regional variation in the total labor demand elasticity. In addition, the means of the labor demand elasticity distributions all fall within the range mentioned in the literature. Our results are also in line with evidence by Revelt and Train (1998) that treating a parameter as a random variable usually increases its mean estimate; this can be seen by comparing the elasticity estimates from step one and step two. An exception is the construction sector.

Once we have information regarding the distributions of the wage elasticities of labor demand, it is possible to get elasticity estimates for each county. Using these estimates we find evidence of a negative relationship between the total wage elasticity of labor demand and the incidence of union membership among workers. This result makes intuitive sense since unions probably make firms less flexible in hiring and firing workers thereby driving down labor demand elasticities. We also find that the presence of a right to work law makes labor demand more elastic. This is also consistent with intuition since a right to work law will reduce the influence of unions at the workplace and firms will become more flexible in their hiring and firing decisions.

The paper proceeds as follows. In section 2 we discuss briefly the theory behind the labor demand function. In section 3 we describe the dataset. In sections 4 and 5 we present the results from the linear and random parameter panel data models . In section 6 we explain how we obtain county specific labor demand elasticity estimates. In section 7 we discuss the relationship between labor demand elasticity and union membership. Finally, in section 8 we conclude by pointing to some applications and possible extensions of our work.

2 Theory

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

$$\frac{\delta \ln L\,(w, Y)}{\delta \ln w} = \eta'_{LL} = - \underbrace{[1 - s_L]\sigma}_{substitution\; effect} - \underbrace{s_L \eta_D}_{scale\; effect} \tag{1}$$

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 demand for the industry, L is the quantity of labor demanded, w is the wage rate, and Y is output.

The first part of the total labor demand elasticity 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 profit maximizing firm's part. 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 captures the "scale effect". As the cost of hiring labor rises, output price increases, which in turn lowers the demand for the industry's output, and hence lowers the industry's labor demand. Hence, the total labor demand elasticity can be viewed as the weighted average of the constant-output labor demand elasticity and the own-price product demand elasticity.

As Hamermesh (1993), Slaughter (2001), and Hasan et al. (2007) point out, the choice of Y will determine whether we are estimating the constant output labor demand elasticity or the total own price labor demand elasticity. If the measure of output embodies the overall industry demand conditions, then we will be estimating the total labor demand elasticity.

3 Data

We use the County Business Patterns (CBP) data set to get data from 1988 to 2010 on the number of establishments, total mid-March employees, and total first quarter payroll by industry for counties in the conterminous U.S. In our dataset an observation refers to an industry-county-year combination.

According to the Census Bureau, in the CBP, "An establishment is a single physical location at which business is conducted or services or industrial operations are performed." An establishment is different from a company or enterprise in that a company might control multiple establishments. A company is controlled by a single organization. In the CBP, the Standard Industry Classification (SIC) system was used to categorize establishments by their primary activity for the period leading up to 1997. From 1998 onwards, the CBP switched to the North American Industry Classification System (NAICS). Even between 1998 and 2010 there were periodic changes made to the NAICS.

In the CBP, data are available at various industry aggregation levels. For this study, we use the 2-digit SIC and 2-digit NAICS industries to create four major industry groups: construction, finance-insurance-real estate-service, manufacturing, and retail. These four industries account on average for 87% of annual total employment in the sample. Table 2 provides our industry aggregation scheme.

Even at the 2-digit industry classification level the census bureau suppresses data for confidentiality reasons. In such cases the census bureau provides an interval for the industry employment level but sets payroll data equal to zero. Such data suppression causes an average annual loss of 1% of total workers in the sample spread across the different industries. Because of this small size we choose to drop observations subject to data suppression.

We calculate the industry wage rate by dividing first quarter payroll by the total number of mid-March employees[1]. The exact formula is shown below. In our notation i, c, t denote industry, county and year, respectively, and s indexes the state in which the county is located,

$$w_{ict} = \left(\frac{CPI_{2010}}{CPI_t} \times \frac{Total\ First\ Quarter\ Payroll_{ict}}{Employees_{ict}} \right) \div 480 \tag{2}$$

where the division by 480 indicates that we assume that an average worker is employed for 480 hours during the first quarter, and 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 share in a state's industry GDP (SGDP) is proportional to the county's share in the total number of industry establishments located in that state. Using this assumption, we impute county industry GDP, which gives us a measure of industry demand conditions. The exact formula is shown below,

[1] Slaughter (2001) also follows the same procedure.

$$Y_{ict} = \left(\frac{PPI_{2010}}{PPI_t} \times \frac{Establishments_{ict}}{\sum\limits_{c} Establishments_{ict}} \times Gross\,State\,Product_{ist} \right) \tag{3}$$

where PPI is the producer price index obtained from the BLS.

In our sample the count of workers from all industries increased from 86,791,257 in 1988 to 108,831,971 in 2010, a growth of approximately 25%. In 1988, the distribution of workers among the different sectors was given as follows: construction 5%, finance-insurance-real estate-service 36%, manufacturing 22%, retail 21%, and others 16%. In the next 23 years the employment levels in the construction, finance-insurance-real estate-service, and retail sectors registered growth rates of 8%, 69%, and 47% respectively. The manufacturing sector during the same period experienced a fall in employment of around 46%. This means that in 2010 the distribution of workers among the different sectors was: construction 5%, finance-insurance-real estate-service 47%, manufacturing 9%, retail 25%, and others 13%. In other words, in the 23 year 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 estate-service, manufacturing, and retail sectors grew by 27%, 133%, 2%, and 80%, respectively. This implies that even though the manufacturing sector lost workers, the remaining workers became more productive. Figures 8 and 8 present yearly values of total national employment and total national real output for the four industries.

The real wage rate ($/hour) in 1988 in the construction, finance-insurance-real estate-service, manufacturing, and retail sectors was 13.78, 11.85, 18.03, and 8.32, respectively. In 2010, the real wage rate in the construction, finance-insurance-real estate-service, manufacturing, and retail sectors increased to 15.72, 15, 19.87, and 8.60, respectively. This means that the real wage rate across the construction, finance-insurance-real estate-service, manufacturing, and retail sectors had growth rates of

14%, 26%, 10%, and 3%, respectively. Figure 3 shows yearly values of the real wage rate.

Table 3 presents some more descriptive statistics for the data at the county level. It reveals that on average the finance-insurance-real estate-service sector dominates county employment followed by the retail and manufacturing sectors. The construction sector employs on average the least number of workers in a county. Table 3 also shows that on average the wage rate is highest in the manufacturing sector and lowest in the retail sector. In fact, the retail wage rate is pretty close to the U.S. federal nominal minimum wage rate of $7.25.

Because of data suppression and natural changes in the employment distribution across counties we end up with an unbalanced panel data set. The construction, finance-insurance-real estate-service, manufacturing, and retail sectors are present in 3075, 3099, 2952, and 3106 distinct counties, respectively. However, only 2037, 2889, 1839, and 2857 counties appear every year in our dataset for the construction, finance-insurance-real estate-service, manufacturing, and retail sectors. The remaining counties appear infrequently.

4 Constant Parameter Panel Data Model

We denote industry, county and year by i, c, t , respectively, and s indexes the state in which the county is located. We specify the labor demand function following Hamermesh (1993), Slaughter (2001), and Hasan et al. (2007), as

$$\ln\left(L_{ict}\right) = \beta_{0is(c)t} + \beta_{1i}\ln\left(w_{ict}\right) + \beta_{2i}\ln\left(Y_{ict}\right) + \vartheta_{ic} + \varepsilon_{ict} \quad (4)$$

where L is employment, w the real wage rate, Y real output, ϑ a time invariant industry specific county fixed effects, and ε is the error term. $\beta_{0is(c)t}$ is a constant that varies by state and year. In the above specification β_{1i} gives the industry specific total wage elasticity of labor demand.

From a purely statistical viewpoint identification of the parameters in equation (4) requires that $\ln(w_{ict})$ and $\ln(Y_{ict})$ be uncorrelated with ϑ_{ic} and ε_{ict}. If this condition fails, we can still identify the parameters by first differencing equation 4 which gets rid of the time invariant county fixed effects. The first differenced version of the labor demand function is given in 5. Now, as long as $\Delta\ln(w_{ict})$ and $\Delta\ln(Y_{ict})$ are uncorrelated with $\Delta\varepsilon_{ict}$, we can use the OLS estimator to estimate the parameters $\Delta\beta_{0is(c)t}, \beta_{1i}, \textit{and}\, \beta_{2i}$. First differencing also implies that the term $\Delta\varepsilon_{ict}$ is less likely to be serially correlated. Note that, by using 5 we cannot estimate the state specific trends, but only the change in the trends,

$$\triangle\ln\left(L_{ict}\right) = \triangle\beta_{0is(c)t} + \beta_{1i}\triangle\ln\left(w_{ict}\right) + \beta_{2i}\triangle\ln\left(Y_{ict}\right) + \triangle\varepsilon_{ict} \tag{5}$$

In economic terms, to claim that β_{1i} measures the total wage elasticity of labor demand we are in fact assuming that market labor supply is perfectly elastic. If this is not the case, then our model will suffer from simultaneity bias since market outcomes are determined by both demand and supply. We believe that a perfectly elastic labor supply is a reasonable assumption given that our unit of observation is an industry at the county level. Slaughter (2001) makes the same assumption in his time series study of 4-digit SIC national manufacturing industries. Slaughter (2001) argues that his industries are disaggregated enough to support his assumption, and points to the fact that almost all the studies cited in Hamermesh (1993) make a similar assumption regarding labor supply. Figure 8 presents our assumption regarding labor supply graphically.

In the labor demand equation, $\beta_{0is(c)t}$ captures the combined state level effects which may drive labor demand in the counties located in that state. For example, among other things, $\beta_{0is(c)t}$ may include state level labor market regulations. Moreover, by allowing the state level constant to vary over time, we can capture changes in such labor market regulations.

The estimation results are presented in Table 4, where we present models with and without $\beta_{0is(c)t}$. We report cluster robust standard errors, where clustering is done at the state level to account for possible correlation of employment across counties within a state (Dube et al., 2010). Based Table 4, the absolute values of the estimates of the total wage elasticity of labor demand for our four industries fall in the interval 0.11-0.32. This is consistent with the estimates presented in Hamermesh (1993). As specification 2 shows in Table 4, the wage elasticity of labor demand does not change much when we drop $\beta_{0is(c)t}$ from the labor demand equation but, as expected, the R^2 drops significantly. In both specifications we see that the construction sector has the highest labor demand elasticity, followed by manufacturing and retail trade. The finance-insurance-real estate-service sector has the lowest labor demand elasticity.

The coefficient for real output is positive and less than one across industries and specifications. We infer from Table 4 that the retail sector is the most sensitive to changes in output followed by the construction, finance-insurance-real estate-service, and manufacturing sectors.

5 Random Parameter Panel Data Model

In the labor demand equation presented in the previous section the coefficient of log wage, β_{1i}, is a constant. This means that 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, since then, the number of parameters to estimate will be greater than the number of observations in the data. To incorporate regional variation in the wage elasticity of labor demand across counties, 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} s' will have the correct sign.

An alternative approach to incorporate heterogeneity in the wage elasticity of labor demand across counties would be to interact $\ln(w_{ict})$ with some variable which we believe affects the wage elasticity of labor demand and which itself varies across counties. However, there are two drawbacks with this approach. One, since multiple factors may influence the wage elasticity of labor demand, the result will crucially depend on the choice of the interaction variables. Two, theory provides little guidance on the choice of the interaction variables.

We believe that a more robust approach is to assume that the parameter β_{1i} is a random variable. Under this approach, 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[2]. In equation 6, the log linear labor demand equation now includes β_{1ic} to incorporate heterogeneity in the wage elasticity of labor demand at the county level. We assume that β_{2i} is a constant.

$$\ln\left(L_{ict}\right) = \beta_{0i} - \beta_{1ic} \ln\left(w_{ict}\right) + \beta_{2i} \ln\left(Y_{ict}\right) + \vartheta_{ic} + \varepsilon_{ict} \tag{6}$$

As Table 4 shows, the results from the constant parameter linear panel data models are not greatly different with or without the inclusion of the state-year dummy

[2]To incorporate time variation in the wage elasticity of labor demand we could split the data into different time periods and estimate separate models for each time period.

interaction variables. Therefore, to simplify our estimation, we choose the log linear labor demand function without the state-year dummy interaction variables.

Again, first differencing removes the county fixed effects and yields the following equation,

$$\triangle \ln(L_{ict}) = -\beta_{1ic}\triangle \ln(w_{ict}) + \beta_{2i}\triangle \ln(Y_{ict}) + \triangle\varepsilon_{ict} \tag{7}$$

We assume that the distribution of $\Delta\varepsilon_{ict}$ conditional on β_{1ic} , $\Delta\ln(w_{ict})$ and $\Delta\ln(Y_{ict})$ is i.i.d $N(0, \sigma^2_{(\varepsilon_i)})$. If the independence assumption for the error terms fails, our estimator is still consistent. However, the standard errors would need to be adjusted for serial correlation.

We assume that β_{1ic} is distributed i.i.d $\ln(N[\beta_{1i}, \exp(\gamma_i)])$ in the population of counties, where β_{1ic} and $\exp(\gamma_i)$ are the mean and variance of β_{1ic} 's natural logarithm. The log normal distribution assures that β_{1ic} is always positive. Note also that $\exp(\gamma_i)$ guarantees a positive value for the shape parameter of the log-normal distribution. The mean and variance of β_{1ic} are given by the following formulas,

$$\bar{\beta}_{1i} = E[\beta_{1ic}] = \exp\left[\beta_{1i} + \frac{\exp(\gamma_i)}{2}\right] \tag{8}$$

$$\sigma^2_{\beta_{1i}} = Var(\beta_{1ic}) = [\exp(\exp(\gamma_i)) - 1]\exp[2\beta_{1i} + \exp(\gamma_i)] \tag{9}$$

The log-likelihood function for the model is presented in Equation 10

$$\ln L(\theta_i) = \sum_c \sum_t \ln\left[\int_0^{+\infty} \phi(\triangle\varepsilon_{ict}(\beta_{1ic}))\,\phi_{Ln}(\beta_{1ic})\,d\beta_{1ic}\right] \tag{10}$$

where θ_i is the vector of parameters we estimate, ϕ is a normal density function with mean zero and variance $\sigma^2_{(\varepsilon_i)}$, and ϕ_{Ln} is a log-normal distribution with mean β_{1i} and variance $\exp(\gamma_i)$.

The log-likelihood function in equation 10 is evaluated by simulation since the integral in the log-likelihood function cannot be computed analytically. The simulation is performed as follows. Given θ_i , we draw a value for β_{1ic} from the log-normal distribution. The draws of β_{1ic} are independent across counties. We then compute the normal density ϕ_{ict} for that draw. We repeat this process R times and find the average ϕ_{ict} . The simulated log-likelihood function is,

$$\ln\, SLL(\theta_i) = \sum_c \sum_t \left(\frac{1}{R} \sum_r \phi_{ictr} \right) \tag{11}$$

where r indexes a draw from the log-normal distribution.

The simulated maximum likelihood estimator is the vector of parameters $\hat{\theta}_i$ that maximize the SLL function. To reduce our computational burden we set the values for β_{2i} and $\sigma^2_{(\varepsilon_i)}$ at those obtained from the linear panel data result presented in Table 4, where $\sigma^2_{(\varepsilon_i)}$ takes the value equal to the variance of the first difference residuals. Given that the number of draws (R) increases faster than $\sqrt{N}$ (the number of cross sectional units), the simulated maximum likelihood estimator retains all the properties of the traditional maximum likelihood estimator (Train, 2009). We use a sample of 1000 random draws for each county to simulate the log likelihood function. We then use the 'Nelder-Mead' algorithm to maximize the simulated log likelihood function[3]. The simulated maximum likelihood estimates are presented in Table 5.

Comparing Tables 4 and 5 we find that for all the industries except construction the random parameter model yields a higher value for the average wage elasticity of

[3]The 'Nelder-Mead' technique is a search algorithm which does not require computations of derivatives. Given the size of our dataset and the need for simulation in computing the integral, we choose the 'Nelder-Mead' algorithm over other commonly used algorithms.

labor demand than the estimates from the linear panel data model. Our finding is consistent with Revelt and Train (1998), who conclude that the mean coefficients in a mixed logit model are consistently bigger than that the fixed coefficients from a standard logit model. This happens because the random parameter model explains some of the variation in the unobserved component of the linear panel data model which arises due to the randomness of the parameter.

Table 5 also shows statistically significant spatial variation in the labor demand elasticity. The manufacturing sector has the highest spatial variation, followed by finance-insurance-real estate-service, retail trade, and construction sectors.

6 County Specific Labor Demand Elasticity

In the previous section we presented estimates of the mean and standard deviation of the log normal distributions which describe the wage elasticity of labor demand for four different industries in the U.S. From these estimates we can calculate, for example, for every industry the proportion of counties which have a wage elasticity of labor demand greater than one. However, we can do better and estimate an average wage elasticity of labor demand for each county. We describe this procedure below based on Train (2009).

Consider Equation 12,

$$\hat{\phi}_{Ln}\left(\beta_{1ic}|\triangle\varepsilon_{ict}\right) \times f\left(\triangle\varepsilon_{ict}\right) = \phi\left(\triangle\varepsilon_{ict}|\beta_{1ic}\right) \times \phi_{Ln}\left(\beta_{1ic}\right), \tag{12}$$

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

Rearranging equation 12 we get,

$$\hat{\phi}_{Ln}\left(\beta_{1ic}|\triangle\varepsilon_{ict}\right)=\frac{\phi\left(\triangle\varepsilon_{ict}|\beta_{1ic}\right)\times\phi_{Ln}\left(\beta_{1ic}\right)}{f\left(\triangle\varepsilon_{ict}\right)} \tag{13}$$

Note that the conditional probability of β_{1ic} will vary over the years because $\triangle\varepsilon_{ict}$ changes from year to year. This implies that we can get $\bar{\beta}_{1ict}$, the average wage elasticity of labor demand for industry i located in county c at year t, using equation 14.

$$\bar{\beta}_{1ict}=\int\beta_{1ic}\hat{\phi}_{Ln}\left(\beta_{1ic};\triangle\varepsilon_{ict}\right)d\beta_{1ic}, \tag{14}$$

which can be rewritten as

$$\bar{\beta}_{1ict}=\int\beta_{1ic}\frac{\phi\left(\triangle\varepsilon_{ict};\beta_{1ic}\right)\times\phi_{Ln}\left(\beta_{1ic}\right)}{f\left(\triangle\varepsilon_{ict}\right)}d\beta_{1ic} \tag{15}$$

The simulated counterpart of $\bar{\beta}_{1ict}$ is $\check{\bar{\beta}}_{1ict}$ which is described by the formula given in equation 16,

$$\check{\bar{\beta}}_{1ict}=\sum_{r}w^{r}\beta^{r} \tag{16}$$

where

$$w^{r}=\frac{\phi\left(\triangle\varepsilon_{ict};\beta_{1ic}\right)}{\sum_{r}\phi\left(\triangle\varepsilon_{ict};\beta_{1ic}^{r}\right)}. \tag{17}$$

Since we assume a time invariant wage elasticity of labor demand, we modify equations 16 and 17 to get $\check{\bar{\beta}}_{1ic}$ as shown below.

$$\check{\bar{\beta}}_{1ic} = \sum_t \sum_r w^{r\prime} \beta^r \tag{18}$$

$$w^{r\prime} = \frac{\phi\left(\triangle\varepsilon_{ict}; \beta^r_{1ic}\right)}{\sum\limits_t \sum\limits_r \phi\left(\triangle\varepsilon_{ict}; \beta^r_{1ic}\right)} \tag{19}$$

We map the county specific total wage elasticity of labor demand for each industry using ArcGIS© (Figures 8, 8, 8 and 8). As the color in the maps changes from yellow to red, it indicates an increasing wage elasticity of labor demand. The white spots in the map are counties for which we have no estimates available.

7 Effect of Union Membership on County Specific Labor Demand Elasticity

In section 5 we mentioned that various factors might induce variation in the wage elasticity of labor demand across counties in the U.S. One such factor might be the incidence of union membership among workers. Intuitively, unions should make firms less flexible in hiring and firing workers in response to wage changes, and, therefore, should exert a negative impact on the absolute value of the total wage elasticity of labor demand. In other words, if there is a significant presence of unions in a state, then following an increase in employment the firms might not be able to reduce employment as much as in a state with lower union presence.

We use an alternative measure of union power by introducing a dummy variable measuring whether a state has implemented a right to work law. 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 non union member worker will enjoy the benefits arising from the union's negotiations with the management. Hence, in a right to work law state, employers will have more flexibility in changing their hiring pattern following a wage movement. As a consequence we will expect the total elasticity of labor demand to be higher in a county that belongs to a state that has the right to work law in place.

To test this hypothesis we obtain data for the years 2001 to 2010 on the percentage of workers in a state belonging to unions from the Bureau of Labor Statistics. We average the union membership data for the ten year period for the lower 48 states and the District of Columbia. The averages are shown in Table 6. According to Table 6, over the ten year period, New York State had the highest average union membership among workers at 26.26%, more than twice the overall average of 11% in the conterminous U.S. during this period; North Carolina had the lowest at 4.26%.

We specify our model as follows:

$$\begin{aligned} \ln\left(\breve{\bar{\beta}}_{1ic}\right) &= \sum_{k=1}^{K} \gamma_k X_{ick} + \delta \ln\left(Average\ Union\ Membership_{s(c)}\right) \\ &\quad + \xi Right\ to\ Work\ Dummy + \varepsilon_{ic} \end{aligned} \tag{20}$$

where average union membership gives us the extent of unionization in a state and X is a set of controls (K) (average total county employment between 2001 to 2010, industry dummy variables, urban dummy). In a different specification, instead of including average union membership as the main independent variable of interest, we include a dummy indicating whether the state has a right to work law in place or not.

The right to work dummy variable has the value of 1 if the state where the county is in has a right to work law in effect. Table 7 shows the right to work states and the year when the statue was enacted and/or the constitution amended. We treat the dummy for right to work having the value 0 for Indiana and Michigan as they became right to work states in 2012. We then specify the model with both the average union membership and right to work dummy included.

All the three models are then estimated with dummy variables for state included in order to account for state fixed effects.

In Table 8 we present regression results where the dependent variable is the log of the absolute value of the county wage elasticity of labor demand in an industry and the independent variable(s) of interest is the log of average state level union membership among workers and/or the right to work dummy. The regression sample pools across all industries as can be seen from equation 20. In the regression equation, we include average total county employment over the ten year period, and a dummy variable to indicate if the county was designated rural or urban in the 2000 U.S. decennial census. We also include industry fixed effects in the regression. In addition to these covariates, specifications 4, 5, 6 in Table 8 include state fixed effects. Across all specifications except specification 3 (with both average union membership and the right to work dummy included, but state dummies excluded) we find that higher union membership among workers in a state tends to lower the absolute value of the county wage elasticity of labor demand. We find that raising union membership by 10% among workers will reduce county wage elasticity of labor demand by 0.05% according to specification 1 (with average union membership included, but the right to work dummy and state dummies excluded). In addition, we find that counties designated urban in the 2000 U.S. decennial census, usually have a lower wage elasticity of labor demand. Counties which have more workers on average, tend to have a more elastic labor demand. In specification (3), where we have both average union membership and right to work binary variable included in our model, but exclude state indicator variables, the effect of union membership becomes positive but not statistically significant.

With the right to work dummy included in our model, we find that the absolute value of the county specific total wage elasticity of labor demand will go up (or the demand for labor will become more elastic) if the state, where a specific county is in, has a right to work law in place. When we include only the right to work dummy in our model and exclude average union membership and state dummy variables, as in specification (2), we find that the total wage elasticity of labor demand is about 0.7% higher in counties belonging to states with a right to work law. When we include only the average union membership variable but not state identifiers, as in specification (3), we find that counties in states with right to work laws have about a 1.1% higher labor demand elasticity. In specification (5), including just the state dummy variables, but not the average union membership tells us that, if a county is in a state with the right to work law in place, then it will have a 5.2% higher labor demand elasticity. If we include average union membership, the right to work dummy, and state indicator variables in our model (specification 6), we find that a 10% rise in average union membership will lower the total wage elasticity of labor demand in a county by 0.18%, and, if the state where the county is situated in has enacted a right to work law, then it will increase the labor demand elasticity by 7.2%.

To summarize, we find in all the specifications except one (not statistically significant) that, with a higher extent of union membership, the county-specific total wage elasticity of labor demand decreases. This implies that, as union penetration rises, the total wage elasticity of labor demand becomes less elastic, or employers become less flexible in their hiring and firing decisions. We find in all specifications that, if a county belongs to a state that has enacted a right to work law, then the county-specific total wage elasticity of labor demand is higher in that county. In other words, if union membership or payment of union membership dues are not mandatory, then the total wage elasticity of labor demand will be higher, or employers will have more flexibility in the hiring and firing decisions.

8 Conclusion

The main goal of this study is to provide a benchmark analysis for the estimation of labor demand elasticities by classifying the United States labor market into different industries. One advantage and rationale for pursuing this study is to be able to investigate and comment on the effects of different external shocks and policy changes on the elasticity of labor demand for different industries, without being restricted to any particular industry or sector within an industry. We estimate the elasticity of labor demand by dividing the entire United States economy into various industry groups. Our unit of observation in this study becomes an industry-county pair in any given year. Using the County Business Patterns (CBP) dataset for the years 1988 to 2010 we provide county[4] specific estimates of the total wage elasticity of labor demand for four industries: construction, finance-insurance-real estate-service, manufacturing, and retail trade. Our estimates are based on a two-step procedure. In step one we estimate linear, constant parameters, panel data models for each industry. Using the results from step one, in step two we estimate again, for each industry, a linear panel data model, but, where the total wage elasticity of labor demand parameter is a random variable having a log normal distribution in the population of counties. We find statistically significant evidence that the total wage elasticity of labor demand exhibits spatial variation within each of the four aggregated industries.

[4] 2943 Counties located in the conterminous U.S.

Our estimates of the county specific total wage elasticities of labor demand can be utilized to investigate the effects of a policy shock, such as a minimum wage law, or of a labor market feature, such as the extent of union membership on the elasticity of labor demand. Our methodology enables us to compare not only the absolute changes in the labor demand elasticity in an industry after a policy change or a change in a labor market feature, but also the relative changes in the labor demand elasticity across industries. We show this by analyzing the effect of union membership and the right to work law on the labor demand elasticity. We find that higher union membership makes the county-specific total wage elasticity of labor demand less elastic, and the presence of a right to work law makes it more elastic.

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Table 1: Elasticity Measurements in the Literature

Study	Description	Data	Time Period	$-\eta'_{LL}$
Nadiri ('68)	U.S. Manufacturing, K held constant	Aggregate, Quarterly, Time Series	1947-64	0.12
Messe ('80)	U.S. private production-worker, KL prices, K held constant	Aggregate, Quarterly, Time Series	1947-74	1.73
Layard & Nickell ('86)	U.K. Aggregate, K held constant	Aggregate, Quarterly, Time Series	1957-83	1.19
		Aggregate, Annual, Time Series	1954-83	0.93
Andrews ('97)	U.K. Aggregate, KLEM prices, K held constant	Aggregate, Annual, Time Series	1950-79	0.51
Burgess ('88)	U.K. Manufacturing, EM prices, K held constant	Aggregate, Quarterly, Time Series	1964-82	1.85
Harris ('90)	New Zealand private worker, K held constant	Aggregate, Quarterly, Time Series	1965-87	0.24
Nickell & Symons ('90)	U.S. Manufacturing, K held constant	Aggregate, Quarterly, Time Series	1962-84	1.92
Symons & Layard ('84)	OECD Manufacturing, LM prices, no Y or K	Aggregate, Quarterly, Time Series	1956-80	1.54
Wadhwani ('87)	U.K. Manufacturing, KLM prices, no Y or K	Aggregate, Quarterly, Time Series	1962-81	0.38
Kennan ('88)	U.S. Manufacturing production-worker, no Y or K	Aggregate, Monthly, Time Series	1948-71	11.58
Begg et al. ('89)	U.K., import prices, no Y or K	Aggregate, Annual, Time Series	1953-85	0.40
Caruth & Oswald ('85)	U.K.Coal Mining, KLE prices, no Y or K	Small Industry, Annual, Time Series	1950-80	1.4
Wadhwani & Wall ('90)	U.K. Manufacturing, ML prices, K held constant	Firms, Panel Data	1974-82	0.53
Benjamin ('92)	Java Farm Labor, L held fixed	Farms, Cross Section	1980	0.30
Blanchflower et al. ('91)	U.K. plants, no Y or K	Plants, Cross Section	1984	0.93
Slaughter ('01)	U.S. Manufacturing Non-production Labor, no K	Aggregate, Annual, Time Series	1961-91	0.65
Hasan et al. ('07)	India Manufacturing, no K	Small Industry, Panel Data	1980-97	0.40

Notes: *Source*- Hamermesh (1993), authors

Table 2: Industry Aggregation Scheme

Name	Industries	SIC	NAICS
Construction (CONS)	Construction	15	23
Finance, Insurance, Real Estate, Service (FISE)	Finance and Insurance; Real Estate and Rental and Leasing; Information; Professional, Scientific, and Technical Services; Management of Companies and Enterprises; Administrative and Support and Waste Management and Remediation Services; Educational Services; Health Care and Social Assistance; Other Services (except Public Administration)	60, 70	51, 52, 53, 54, 55, 56, 61, 62, 81
Manufacturing (MANU)	Manufacturing	20	31-33
Retail Trade (RETA)	Retail Trade; Arts, Entertainment, and Recreation; Accommodation and Food Services	52	44, 45, 71, 72

Table 3: Summary Statistics

	mean	sd	iqr	min	max	count
Construction						
Employment	2031.9	6779.1	1070	1	178869	64826
Wage	14.6	4.73	5.75	0.61	111.0	64826
Output	192.4	560.3	116.8	1.13	17412.1	64826
Finance, Insurance,Real Estate, Service						
Employment	15087.9	65559.1	5488	1	1987415	70162
Wage	13.5	4.40	4.22	0.63	103.2	70162
Output	1772.4	7631.0	747.0	1.05	287127.8	70162
Manufacturing						
Employment	6068.5	19922.0	4369	2	909836	60298
Wage	18.9	6.18	7.36	1.54	77.4	60298
Output	684.0	2278.5	403.1	3.91	88393.7	60298
Retail						
Employment	7839.7	25965.9	4338	1	853649	70484
Wage	8.39	1.60	1.67	0.99	50.2	70484
Output	403.0	1465.7	217.6	1.09	64728.4	70484

Note: IQR- Interquartile Range

Real Wage in terms of 2010 dollars: Real Wage(t)= Wage(t)*(CPI(2010)/CPI(t))

Table 4: Results from Constant Parameter Panel Data Model

Industry	β_{1i} $\triangle log(wage)$ (1)	(2)	β_{2i} $\triangle log(output)$ (1)	(2)	R^2 (1)	(2)	Observations
Construction	-0.32	-0.29	0.59	0.58	0.24	0.16	59615
	[0.02]	[0.02]	[0.03]	[0.02]			
	(-13.46)	(-12.73)	(21.75)	(25.86)			
Fin./Ins./Real Est./Service	-0.11	-0.13	0.48	0.47	0.36	0.32	66707
	[0.03]	[0.03]	[0.01]	[0.01]			
	(-3.91)	(-4.82)	(32.71)	(32.84)			
Manufacturing	-0.23	-0.22	0.42	0.27	0.16	0.06	55961
	[0.03]	[0.03]	[0.02]	[0.02]			
	(-7.26)	(-7.13)	(19.21)	(11.88)			
Retail Trade	-0.23	-0.20	0.88	0.69	0.50	0.37	66945
	[0.04]	[0.04]	[0.02]	[0.02]			
	(-5.68)	(-5.06)	(45.08)	(30.07)			
State Dummy $\times$Year Dummy	$\surd$	$\times$	$\surd$	$\times$	$\surd$	$\times$	

Notes: Dependent Variable: $\triangle log\,(L_{ict})$
(1): Includes state dummy and year dummy interactions
(2): Doesn't include state dummy and year dummy interactions
Cluster Robust Standard Errors in brackets; T statistics in parentheses
Cluster ID is State

Table 5: Results from Random Parameter Panel Data Model

Industry	$\overline{\beta}_{1i}$	$\sqrt{\sigma^2_{\beta_{1i}}}$	β_{1i}	γ_i	β_{2i}	$\sigma^2_{\varepsilon_i}$
Construction	0.08	0.01	-2.47	0.48	0.59	0.04
			(-52.98)	(30.81)		
Fin./Ins./Real Est./Service	0.34	3.26	-3.34	0.75	0.48	0.04
			(-38.98)	(41.76)		
Manufacturing	0.38	3.97	-3.32	0.77	0.42	0.03
			(-40.17)	(42.53)		
Retail Trade	0.35	0.98	-2.15	0.39	0.88	0.01
			(-50.79)	(27.09)		

Notes: $\overline{\beta}_{1ic}$= Mean of log normal distribution for β_{1ic}= $exp\left[\beta_{1i} + 0.5exp\left(\gamma_i\right)^2\right]$
$\sqrt{\sigma^2_{\beta_{1i}}}$ = Standard deviation of log normal distribution for β_{1ic}
$= exp\left[exp\left(\gamma_i\right)^2 - 1\right] exp\left[2\beta_{1i} + exp\left(\gamma_i\right)^2\right]$
T statistics in parenthesis
β_{2i} and $\sigma^2_{\varepsilon_i}$ are fixed during estimation

Table 6: Average Union Membership Among Workers by State

FIPS State	State Name	Mean Union Mbrshp (%)	FIPS State	State Name	Mean Union Mbrshp (%)
1	ALABAMA	10.83	31	NEBRASKA	10.41
4	ARIZONA	7.83	32	NEVADA	16.80
5	ARKANSAS	6.05	33	NEW HAMPSHIRE	11.63
6	CALIFORNIA	18.13	34	NEW JERSEY	20.00
8	COLORADO	9.15	35	NEW MEXICO	9.96
9	CONNECTICUT	16.97	36	NEW YORK	26.26
10	DELAWARE	12.76	37	NORTH CAROLINA	4.26
11	DISTRICT OF COLUMBIA	14.01	38	NORTH DAKOTA	8.66
12	FLORIDA	7.56	39	OHIO	16.36
13	GEORGIA	6.23	40	OKLAHOMA	8.10
16	IDAHO	7.64	41	OREGON	16.70
17	ILLINOIS	17.73	42	PENNSYLVANIA	16.14
18	INDIANA	13.20	44	RHODE ISLAND	17.43
19	IOWA	13.73	45	SOUTH CAROLINA	5.18
20	KANSAS	9.66	46	SOUTH DAKOTA	7.01
21	KENTUCKY	11.29	47	TENNESSEE	7.46
22	LOUISIANA	7.57	48	TEXAS	6.45
23	MAINE	14.10	49	UTAH	7.27
24	MARYLAND	14.68	50	VERMONT	12.65
25	MASSACHUSETTS	15.68	51	VIRGINIA	6.13
26	MICHIGAN	20.41	53	WASHINGTON	20.56
27	MINNESOTA	17.05	54	WEST VIRGINIA	15.10
28	MISSISSIPPI	7.50	55	WISCONSIN	16.00
29	MISSOURI	12.73	56	WYOMING	9.39
30	MONTANA	14.93			

Notes: Source- Bureau of Labor Statistics, authors' calculations

Table 7: States with Right to Work Laws

FIPS State	State Name	Statue Enactment	Constitutional Amendment
1	ALABAMA	1953	
4	ARIZONA	1947	1946
5	ARKANSAS	1947	1944
12	FLORIDA	1943	1968
13	GEORGIA	1947	
16	IDAHO	1985	
18	INDIANA	2012	
19	IOWA	1947	
20	KANSAS		1958
22	LOUISIANA	1976	
26	MICHIGAN	2012	
28	MISSISSIPPI	1954	1960
31	NEBRASKA	1947	1946
32	NEVADA	1951	1952
37	NORTH CAROLINA	1947	
38	NORTH DAKOTA	1947	1948
40	OKLAHOMA	2001	2001
45	SOUTH CAROLINA	1954	
46	SOUTH DAKOTA	1947	1946
47	TENNESSEE	1947	
48	TEXAS	1993	
49	UTAH	1955	
51	VIRGINIA	1947	
56	WYOMING	1963	

Notes: Source- National Conference of State Legislatures

Table 8: Effect of Union Membership and Right to Work Law on Labor Demand Elasticity

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log of Average State Union Membership	-0.005		0.005	-0.016		-0.018
	[0.004]		[0.007]	[0.001]		[0.001]
	(-1.15)		(0.74)	(-16.11)		(-31.52)
Right to Work Dummy		0.007	0.011		0.052	0.072
		[0.003]	[0.005]		[0.001]	[0.002]
		(2.08)	(2.00)		(43.23)	(31.10)
Log of Average Employment	0.020	0.020	0.020	0.020	0.020	0.020
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
	(14.02)	(14.59)	(14.27)	(14.80)	(14.80)	(14.80)
Urban Dummy	-0.008	-0.008	-0.008	-0.006	-0.006	-0.006
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
	(-2.55)	(-2.66)	(-2.60)	(-2.02)	(-2.02)	(-2.02)
State Dummy	×	×	×	√	√	√
R^2	0.415	0.415	0.419	0.419	0.419	0.419
Observations	11772	11772	11772	11772	11772	11772

Notes: Dependent Variable: log of absolute value of labor demand elasticity. Industry fixed effects are included

Columns 1,2,3: Don't include state dummy

Columns 4,5,6: Include state dummy

Cluster Robust Standard Errors in brackets; T statistics in parentheses; Cluster ID is State

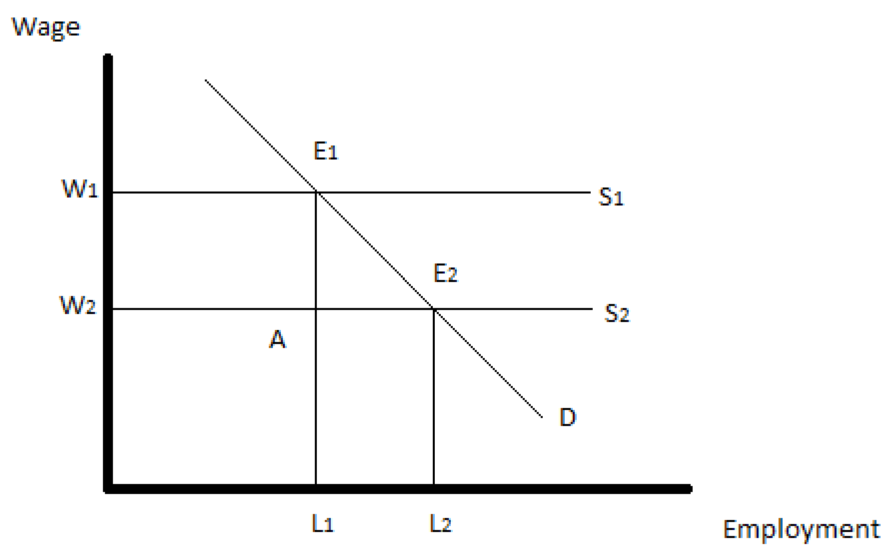

Figure 1: Infinitely Elastic Labor Supply (Hamermesh, 1993)

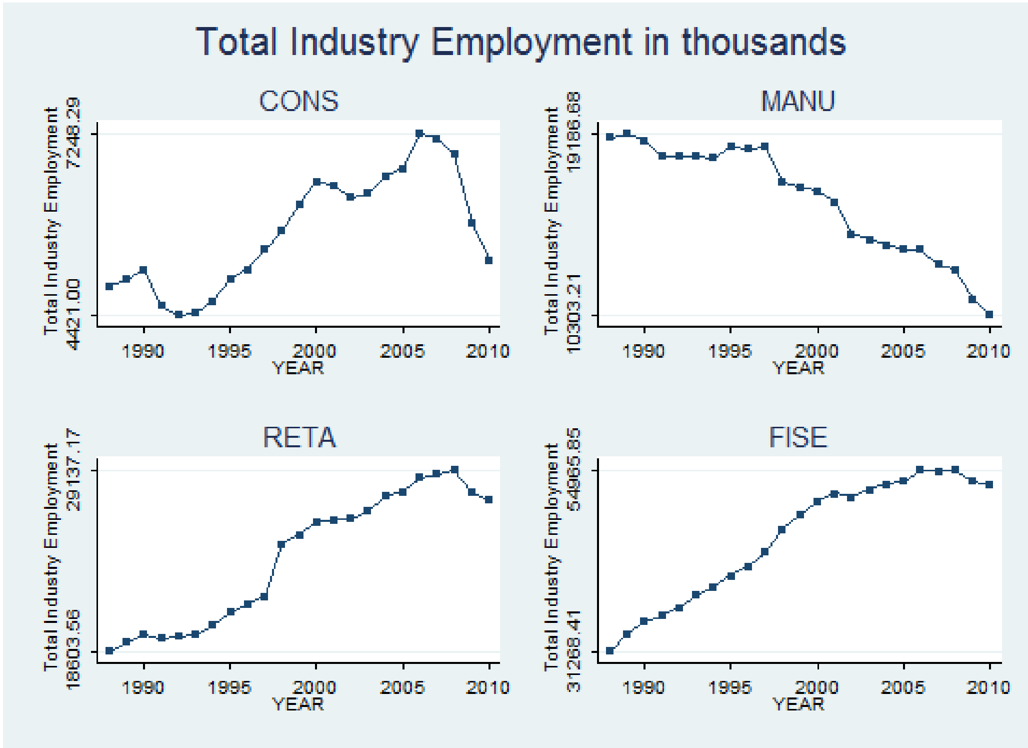

Figure 2: Total Industry Employment in Thousands

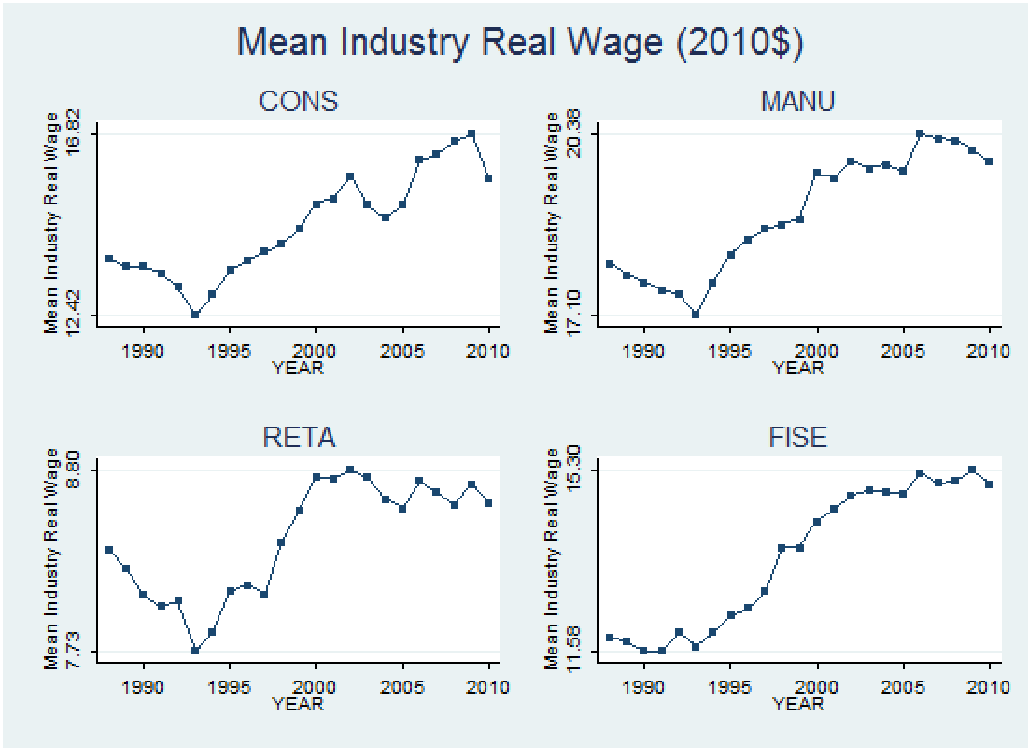

Figure 3: Mean Industry Wage Rate for the United States

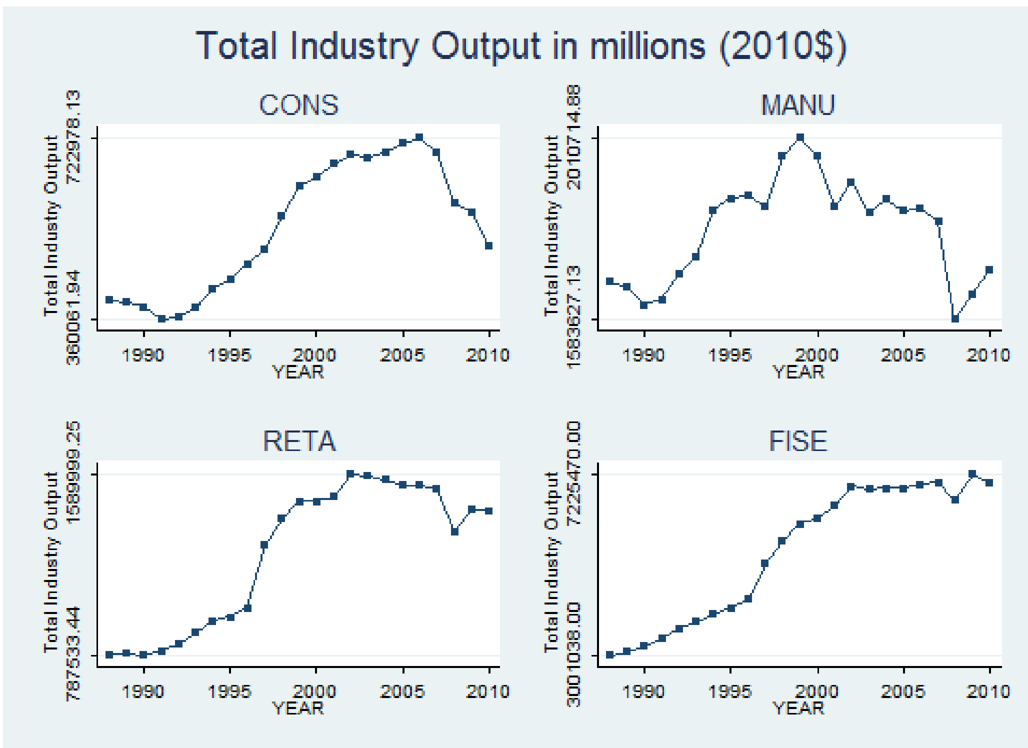

Figure 4: Mean Industry Output for the United States

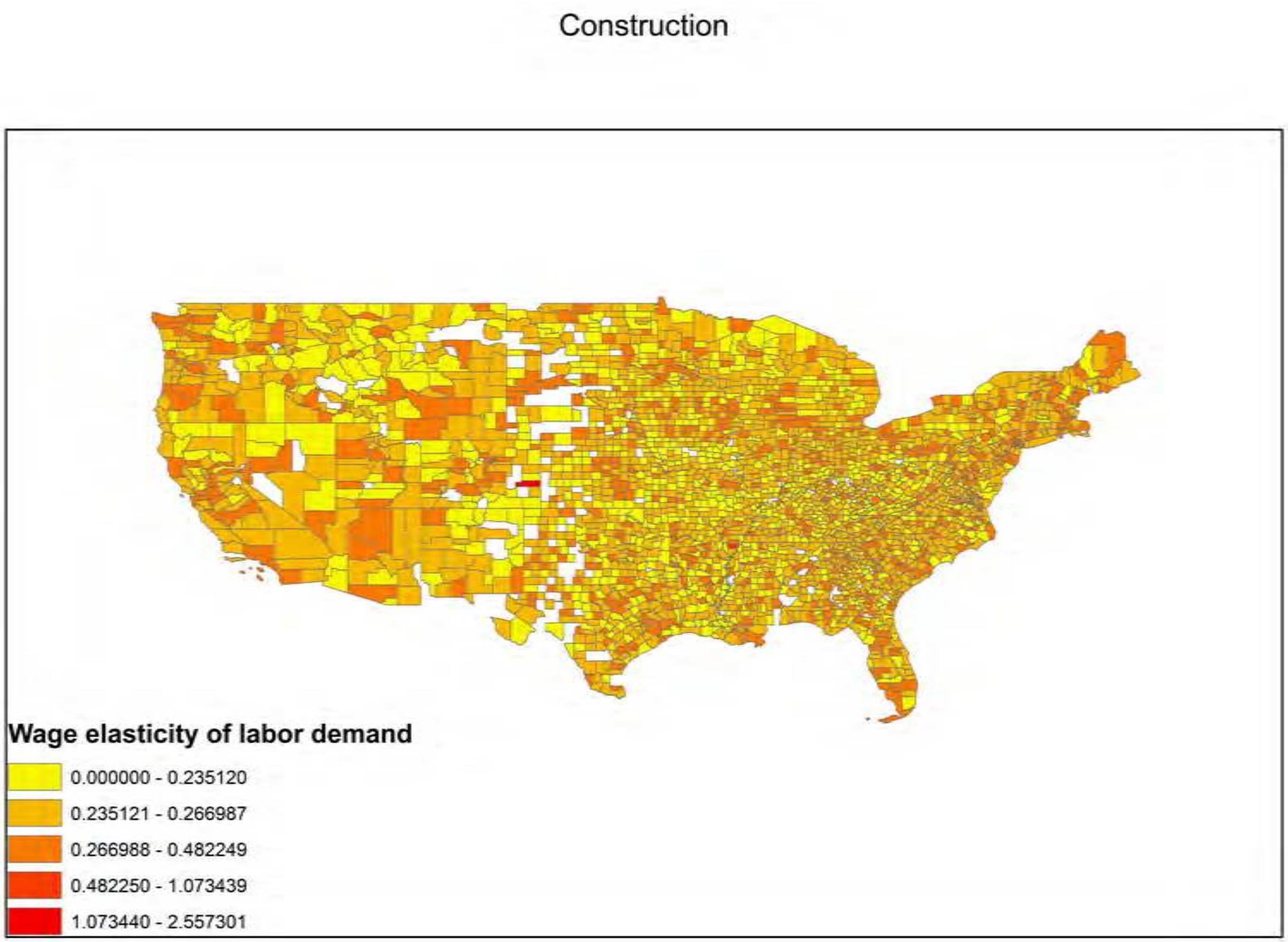

Figure 5: County-wide Distribution of Labor Demand Elasticity in Construction

FIRE and Service

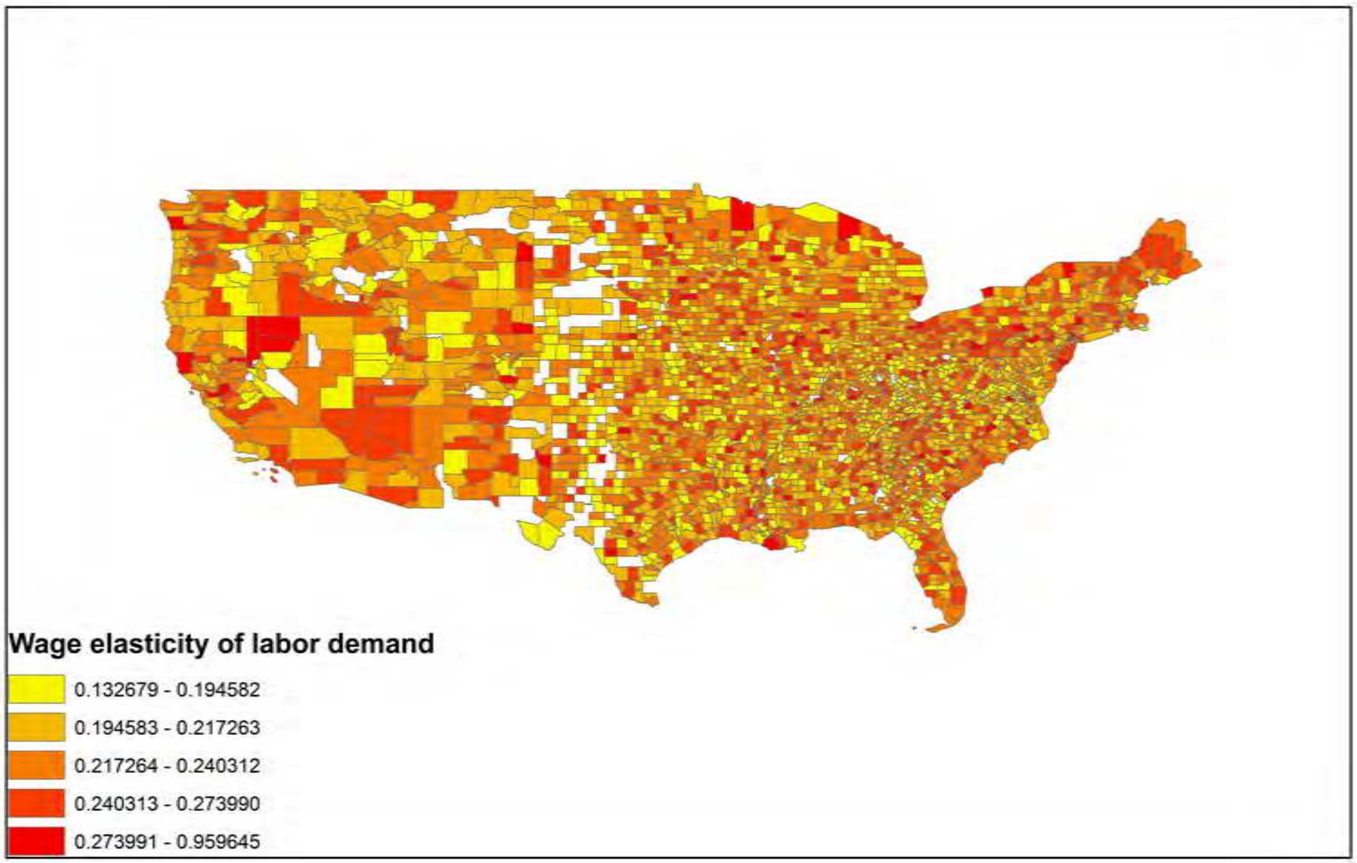

Figure 6: County-wide Distribution of Labor Demand Elasticity in Finance, Insurance, Real Estate, Service

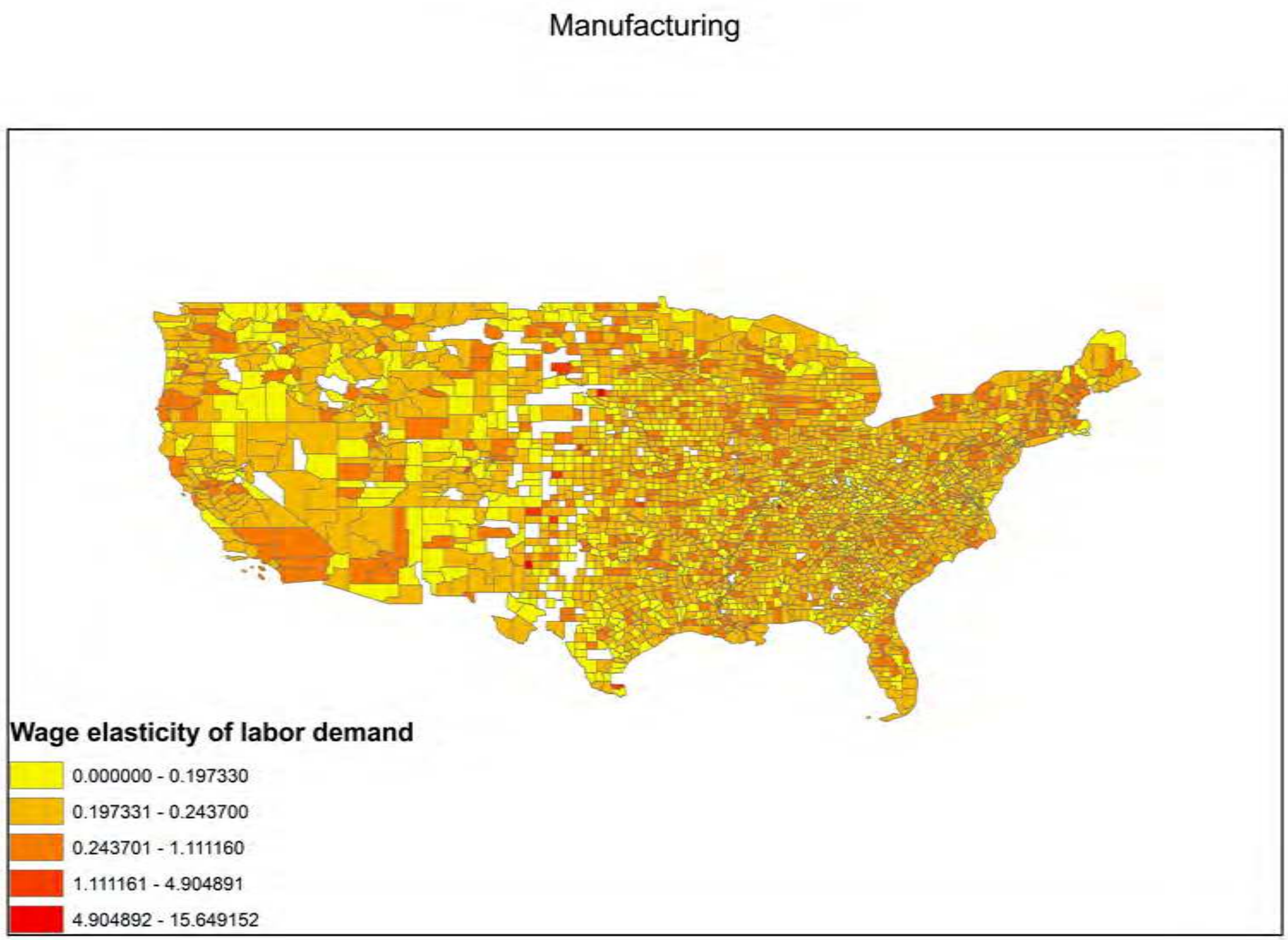

Figure 7: County-wide Distribution of Labor Demand Elasticity in Manufacturing

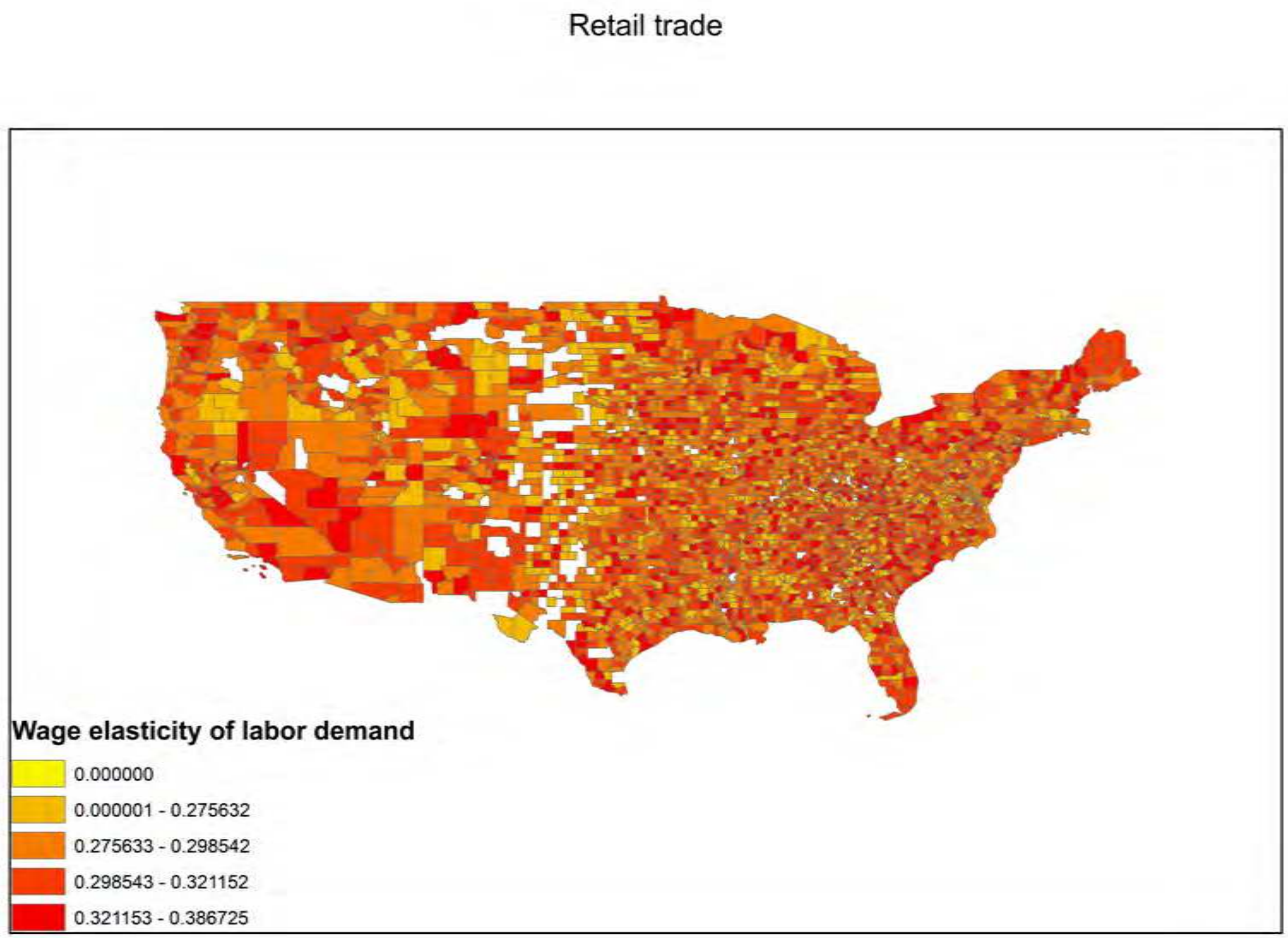

Figure 8: County-wide Distribution of Labor Demand Elasticity in Retail