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Effects of Industrial Diversity on Economic Stability: A Panel GARCH Process to Predict Economic Stability

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This paper studies the relationship between industry diversity and economic stability. The economic stability has been estimated using a panel-GARCH model. Our sample consists of US county-level data for the period 2003 to 2017. The results suggest that industry diversity improves economic stability and reduces a region's unemployment rate. However, this study finds a negative relationship between industry diversity and economic growth. Although diversity negatively affects economic growth, it minimizes income loss when the nation falls into an economic recession. Therefore, we cannot conclude a tradeoff between economic stability and economic growth. It is possible that a region can achieve both stability and growth together through industry diversification. This paper also explores that the effects of diversity on economic stability, unemployment rate, and economic growth may vary between different counties depending on their metro or non-metro status. Thus, this paper suggests that policymakers may choose industry diversification as a strategy to achieve long-run economic stability and precaution against an unexpected economic downturn.

Keywords: Diversity, Stability, Panel GARCH, Income Volatility, Recession, Economic Growth, Industry, Herfindahl, Hachman.

JEL Classifications: O

1 Introduction

We study the relationship between industrial diversity and economic stability, where economic stability is measured by income volatility. We also look at the effects of industrial diversity on the unemployment rate and alternatively on economic growth measured by income per capita. The goal of economic stability is an important issue in regional economic development. A commonly expressed policy goal by local officials is to reduce dependence on specific

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industries by diversifying the economy. Websites aimed at the general public tout diversification as important for economic recovery after a recession or to promote growth (Christopher, 2018; Hales, 2016). The belief is that industry diversification reduces the vulnerability of an economic activity in a local economy. Consequently, a common goal of regional policymakers is to recruit new industries to diversify the local economic base. For example, the 2021 New Mexico legislative session passed Senate Bill 112 establishing the Economic Sustainability Task Force with the goal of developing policy to diversify the New Mexico economy away from oil and gas production (Stewart, 2021). Because of the popularity of economic diversity with policymakers and the public, the literature in this area is large (see, for example, Kort, 1981; Smith and Gibson, 1988; Malizia and Ke, 1993; Dissart, 2003; Pede, 2013; Deller and Watson, 2016a; 2016b). We contribute to this literature by using a panel data fixed effects model that allows us to study the dynamic interaction between industrial diversification and economic stability over time. We apply our model to a panel of U.S. counties for the time period 2003 to 2017. Whether local policymakers should seek to diversify or whether instead, they should specialize to take advantage of regional comparative advantage is an open question with important policy implications that we hope to help address.

Despite the importance placed on diversity by policymakers and economic development specialists, it is not necessarily true that increased industrial diversification will increase income stability. Consider the problem facing a local government official seeking to minimize volatility in per capita income. They have a set of policies that can be used to promote or discourage production in a specific industry. A partial list of these sorts of policies includes tax policy, subsidies, regulation, loan guarantees, and direct lending. The official's problem is to use these policies to manipulate production in particular industries so as to minimize variance in per capita output:

$$\min_{\gamma_i} \sigma_{\gamma}^2 = w^T \Sigma_{\gamma} w \qquad s.t. \sum w_i = 1 \tag{P1}$$

where σ_{γ}^2 is the variance of output, γ_i is income in industry *i*, *w* is a vector of output shares, Σ_{γ} is the income variance-covariance matrix, and $w_i = \gamma_i / \sum \gamma_j$ is the income share of industry *i*. As is well known, the solution to a problem similar to (P1) often requires the concentration in two areas with the two industries having negative covariance. That is, minimalizing (P1) may result in less industry diversity, not more diversity, than the industrial mix that would evolve without intervention.

To get further insight into this issue, consider the derivative of σ_{γ}^2 with respect to γ_i:

$$\frac{d\sigma_{\gamma}^2}{d\gamma_i} = \sum_j 2 w_j \sigma_{ij} \frac{\partial w_j}{\partial w_i} \frac{\partial w_i}{\partial \gamma_i} \tag{P2}$$

where σ_{ij} is the covariance between income in an industry i with income in industry j if $i \neq j$ and is the variance of γ_i if $i = j$. This formula is ambiguous in sign, in that a change in σ_γ^2 depends on the sign and size of the covariances. Strongly countercyclical industries will reduce income volatility while strongly cyclical industries increase it. Actual policies adopted by the local government do not aim to minimize volatility but to increase employment in politically favored target industries. The implementation of such policies may increase volatility. For example, the U.S. state of Oregon in the 1980s and 1990s adopted a policy aimed at promoting expansion in high-tech industries at the expense of fishing, logging, and agriculture only faced a sharp downturn during the 2001 tech-driven recession (Lehner, 2019).

Equation (P2) shows that the impact of industrial diversity on economic stability is ambiguous. Still, the assumption among practitioners and policymakers is that less dependence on a single industry will reduce economic volatility, see e.g., (Boyd, 2021). The argument is that a region that has many industry sectors with a significant number of employees so that the region's economy is not as dependent on one specific sector's performance so will be more stable. In fact, this assumption is supported by empirical studies (Deller & Watson, 2016a, 2016b; Dissart, 2003; Kort, 1981; Malizia & Ke, 1993; Pede, 2013; Smith & Gibson, 1988). If one industry is adversely affected by a recession, other industry sectors will offset the overall economy from falling down. Therefore, if we find a significant positive relationship between industry diversity and economic stability, we can conclude that greater stability can be achieved in an economically volatile region through industry diversity. Similarly, a negative relationship between industry diversity and the unemployment rate indicates that we can minimize employment loss during a recession through industry diversity. Therefore, this study will also find the relationships between industry diversity and the unemployment rate.

Researchers mostly prefer to estimate economic growth as the measure of the economic performance of a region. However, very few researchers have rather considered estimating the economic stability (income volatility). Economic stability implies that employment and income in a region are not subject to extreme swings over a business cycle (Smith & Gibson, 1988). Some recent papers have observed that diversity is spatially correlated with economic performance where economic performance is estimated using Regional Economic Instability (REI) model or otherwise using the Variance Mean Ratio (VMR) model (Chen, 2020; Deller & Watson, 2016b). Although VMR and REI both are strong methods that can estimate long-term volatility, they fail to generate a yearly variance. A Panel GARCH model can solve the issue and can estimate predicted volatility for each year. Thus, we estimate income volatility using a panel-GARCH model. We collected our data from 3079 counties of 48 adjacent states in the US over 15 years from 2003 to 2017 to estimate our model. The objective is to use this predicted income volatility as the indicator for economic stability. Finally, we use this indicator in our fixed effects model as the response variable and industrial diversity as the predictor to observe the relationship between industry diversity and economic stability. We also look at the relationship between the unemployment rate and per capita income growth with industrial diversity. Finally, this paper will observe if this relationship varies with a county's metro and non-metro status, and recommend what strategy a county should follow based on the findings.

Measures of Industry Diversity

We are proposing two different methods for measuring industry diversity: the Herfindahl-Hirschman index (Naldi & Flamini, 2014) and the Hachman index (Hachman, 1994). Herfindahl-Hirschman index has been used by a number of researchers as a measure of industrial diversification (Deller & Watson, 2016a, 2016b; Pallares & Adkisson, 2017). The Herfindahl-Hirschman index for industry *i* of region *r* in time period *t* is given by:

$$HerfIndx_{irt} = \sum_{i=1}^{Z} S_{irt}^2 \text{, with } S_{irt} = \frac{E_{irt}}{E_{rt}} \tag{1}$$

where E_{irt} is the level of employment of industry i in region r at time t, $E_{rt} = \sum_r E_{it}$ is the total employment in region r during time t, and, S_{irt} is the share of employment in industry i in region r during time t. Thus, the Herfindahl-Hirschman index squares the industry employment share and estimates industry concentration by summing up all industry employment shares (Jacquemin & Berry, 1979). The value of the Herfindahl-Hirschman index ranges between $\left({}^{1}/_{Z}\right)^2$ and 1, where Z is the number of industries in the economy under consideration. A value of 1 occurs when a single industry employs all workers meaning maximum concentration. The index is minimized for a given number of industries if each industry has the same number of employees; meaning that each industry will have 1/Z$^{\text{th}}$ share of total employees. A smaller value of the Herfindahl index explains greater diversity.

Another popular method of measuring industry diversity is known as the Hachman index. This measurement is very useful since it compares the industry share of a region with a base region or reference area. The United States is the base region for this study. We will use the following formula to estimate the Hachman diversity index, which Frank Hachman first published in the Bureau of Business and Economic Research (Hachman, 1994).

$$HachIndx_{irt} = \frac{1}{\sum_{i=1}^{Z}\left[\left(\frac{E_{irt}/E_{rt}}{E_{int}/E_{nt}}\right) \times \left({}^{E_{irt}}/_{E_{rt}}\right)\right]} = \frac{1}{\sum_{i=1}^{Z}\left[\left({}^{S_{irt}}/_{S_{int}}\right) \times S_{irt}\right]} = \frac{1}{\sum_{i=1}^{Z}(LQ_{irt} \times S_{irt})} \tag{2}$$

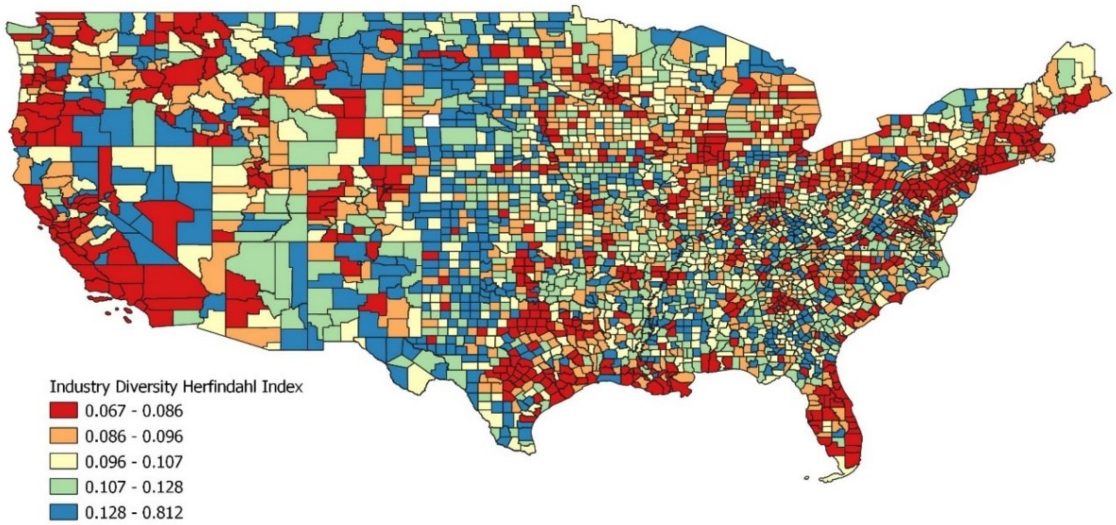
Here E_{int} is the industry i total employment in overall economy and E_{nt} is the total employment in the base region at time t. The subscript n indicates the national employment (i,e total US employment). S_{int} is the share of employment in industry i of the national economy respectively. The ratio between the employment share of industry i in a region r and the employment share of industry i in the reference area $\left({}^{S_{irt}}/_{S_{int}}\right)$ is the location quotient industry i in a region r (LQ_{irt}). Changes in employment in industry i for any region $k \neq i$ may affect the employment share of industry i nationally if it is one of the major industries in that region. That should also affect the Hachman index in region r if that industry gains or loses a significant number of employees.

The Hachman index value ranges from 0 to 1. However, unlike the Herfindahl index, a higher value of the Hachman index represents greater diversity, and a lower value close to 0 represents greater concentration. The Hachman index's assumption suggests that larger economies will be more economically diverse than smaller economies. The national economy (i,e – the reference area's economy) is considered the largest economy compared to any other regions' economy within that nation because the national economy includes all industries' production and employment from all regions (counties for this study). Therefore, the Hachman index assumes the base region is the most diversified region with a value of 1. A region/county with a Hachman Index value of 1 indicates that the region has the exact same industry employment structure as the US (Adkisson & Noor, 2018). On the other hand, a region with a Hachman index value of 0 means the region has an entirely different industry employment structure than the nation. Therefore, we expect to observe opposite signs between Herfindahl-Hirschman index estimates and Hachman index estimates in our industry diversity and economic stability model.

Figure 1 and Figure 2 depict US county maps based on the average value of the Herfindahl-Hirschman index and Hachman Index for the period 2003 to 2017. To create these maps, we use the county-level industry employment data from the regional industry interactive data, Bureau of Economic Analysis (BEA) website at two digits NAICS sectors, which is for 21 industries.[1] Red color counties in Figure 1 indicate the lower Herfindahl index values or highly diversified counties, and blue color counties have less diversity. On the other hand, Figure 2 shows the blue color counties have the higher Hachman index values or greater diversity, while the red color counties have less industry diversity.

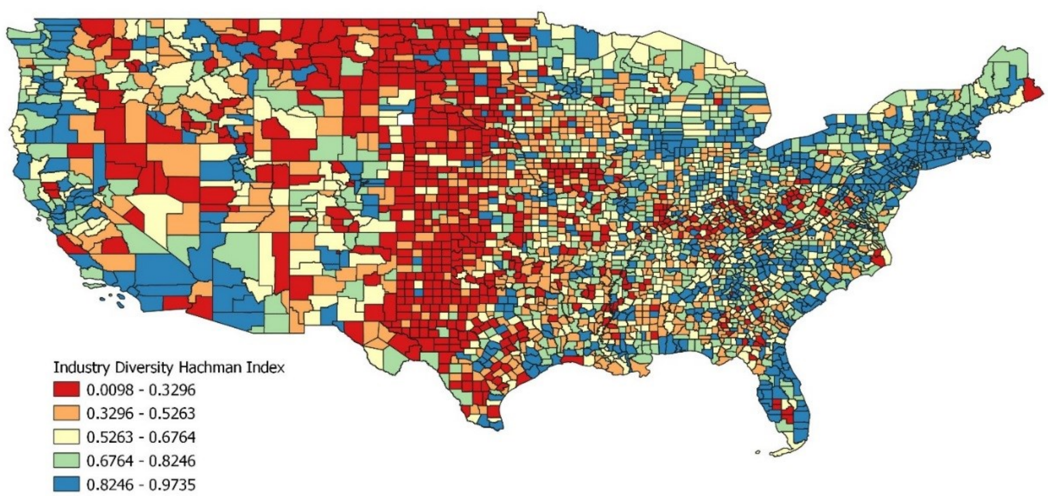
[1] Many researchers use county industry employment data from the Bureau of Labor Statistics (BLS) website. estimated index value might differ from their estimated index values since BEA and BLS use different techniques to record employment data on their websites.

Figure 1. County Industry Diversity Map (Using the Herfindahl Index)



Note: Authors have created this map in GIS. The above map shows industry diversity for US counties which is estimated using the Herfindahl Hirschman index. As the color gets red to blue, industry diversity declines. 20% of counties belong to the red color group which indicates regions with the low Herfindahl index value or greater industrial diversity.

Figure 2. County Industry Diversity Map (Using the Hachman Index)



Note: Authors have created this map in GIS. The map shows industry diversity for US counties which is estimated using the Hachman index. Since the Hachman index is the opposite of the Herfindahl index, the higher value expresses greater industry diversity. Thus, Blue color counties have greater diversity. As the color moves from blue to red on the map, industry diversity decreases. In this map, 20% of counties belong to the group of Blue counties which indicates regions with the high industrial diversity estimated using the Hachman Index.

Measuring Economic Stability

In this section, we introduce the main contribution of this paper, which is the application of a panel-GARCH approach to estimate economic volatility. Specifically, we estimate a GARCH(1,1) to create a time series that allows for variation in income over time. Before turning to the specifics concerning the panel-GARCH, a number of measures of stability have been suggested in the literature. Previous studies typically used one of three measures of volatility. The first of these is the Regional Economic Instability (REI) (Brewer & Moomaw, 1986; Brewery, 1985; Kort, 1981; Malizia & Ke, 1993). A second approach used Deller and Watson, 2016a; 2016b Variance-Mean ratio (VMR) method used to estimate economic stability using, looking at four different stability indicators: unemployment rate, population to employment ratio, the concentration of establishments, and average weekly wages. A third measure, borrowed from finance is the Portfolio Variance (PV) (Kurre & Woodruff III, 1995; Smith & Gibson, 1988).

REI, VMR, and PV are limited when using Panel data in that they provide a single value over the entire time sample. That volatility is constant over time is a strict assumption that may not be valid. Our approach relaxes the assumption of constant volatility by estimating a GARCH (1,1). This allows us to construct a volatility measure that changes over time as well as by observational unit. From the GARCH process, we can get the yearly predicted volatility of per capita income, which will be used as the measure of economic stability in this study. Although our panel data contains pretty large cross-section data of 3079 counties, we have limited time series data (15 years) for each county. Therefore, we limited our lagged values and perform a Panel GARCH (1, 1) model to avoid loss of more degrees of freedom. At first, we detrend the real income data with log transformation. Then we perform a fixed effects model to capture the individual effect and estimate the Panel GARCH model. Therefore, estimating a GARCH (1, 1) model in our panel data will be sufficient rather than using other GARCH models (Skrabic & Arneric, 2019). The application of the GARCH model to panel data is relatively rare in the literature (Cermeño & Grier, 2000, 2006; Cermeño & Suleman, 2014; Lee, 2010; Pakel et al., 2011). We know of no case in which a GARCH model has been used in the context of studying the relationship between industrial diversity and economic stability.

The derivation of the model is given in detail for the real per capita income. To estimate the GARCH(1,1), the first step requires estimating a Dynamic Panel Data (DPD) model from which is extracted error terms (Cermeño & Suleman, 2014):

$$Inc_{rt} = \mu_r + \delta Inc_{r,t-1} + \varepsilon_{rt} \tag{3}$$

where Inc_{rt} is the real personal income per capita in region *r* during time *t.* The Greek letter μ_r captures an individual specific effect, ε_{rt} is the random error terms, and δ is a parameter to be estimated. We assume a balanced panel dataset with $\varepsilon_{rt} \sim N(0, \Omega_{rt})$. This implies:

$$E\left(\varepsilon_{rt}^2 \middle| \Psi_{r,t-1}\right) = \sigma_{rt}^2 \tag{4}$$

The above assumption is the general condition to define the very simple form of the conditional variance process. Where σ_{rt}^2 is the variance of the model conditioned to $\Psi_{r,t-1}$ which is the historical information set for region r at time t – 1. Therefore, if we follow the (Bollerslev, 1986), the above equation (4) is the equivalent to the following equation which is known as the GARCH variance model:

$$\sigma_{rt}^2 = \omega_r + \alpha\varepsilon_{rt-1}^2 + \beta\sigma_{rt-1}^2 \tag{5}$$

Since, σ_{rt}^2 is the conditional variance of income, we can rename it as the income volatility and replace σ_{rt}^2 to *IncVol* in the following equation (6).

$$IncVol_{rt} = \omega_r + \alpha\varepsilon_{r,t-1}^2 + \beta IncVol_{r,t-1} \tag{6}$$

where *IncVol* is the conditional variance of real personal income per capita and is our measure of income volatility. The variance is conditional on its past error square and past variance terms. Where α *and* β are the GARCH parameters and ω is a constant term. A large value of $IncVol_{it}$ indicates low economic stability in a region and vice versa. Additionally, the 2010 GDP deflator value has been used to adjust 2001 to 2017 per capita income data. Finally, this predicted income volatility will be used as the dependent variable in our panel data model.

When the error term, ε_{rt}, is normally distributed, we can write the GARCH (1, 1) process as follows:

$$f\left(\frac{Inc_{rt}}{Inc_{r,t-1}}, \mu_r, \delta, \alpha, \beta\right) \tag{7}$$

$$= (2\pi)^{-\frac{NT}{2}}\Omega_{it}^{\left(-\frac{1}{2}\right)} \exp^{\left(\frac{-1}{2}\right)(Inc_{rt} - \mu_r - Inc_{r,t-1}\delta)' \times \Omega_{rt}^{-1}(Inc_{rt} - \mu_r - Inc_{r,t-1}\delta)}$$

N is the total number of regions and T is the time. From equation 7 we can establish the following log-likelihood function:

$$l = -\left(\frac{NT}{2}\right)\ln(2\pi) - \left(\frac{1}{2}\right)\sum_{r=1}^{N}\sum_{t=1}^{T}\ln(\Omega_{rt}) - \left(\frac{1}{2}\right)\sum_{r=1}^{N}\sum_{t=1}^{T}\left(Inc_{rt} - \mu_r - Inc_{r,t-1}\delta\right)'\Omega_{rt}^{-1}\left(Inc_{rt} - \mu_r - Inc_{r,t-1}\delta\right) \tag{8}$$

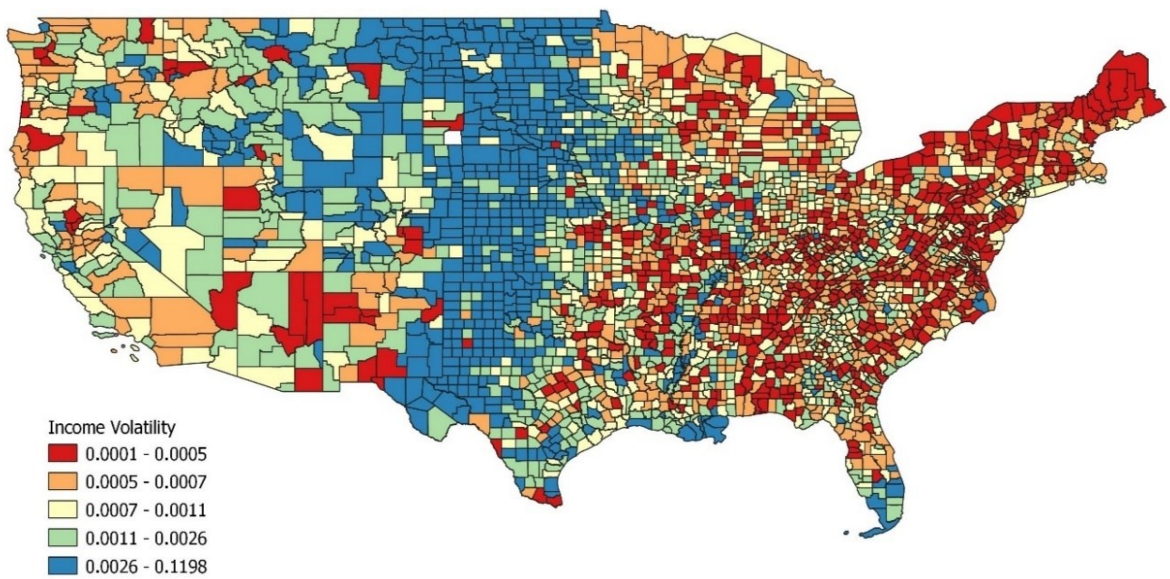
Equation 8 can be rewritten in a non-matrix format which is given in the following equation:

$$l = -\left(\frac{NT}{2}\right)\ln(2\pi) - \left(\frac{1}{2}\right)\sum_{r=1}^{N}\sum_{t=1}^{T}\ln(\sigma_{rt}^2) - \left(\frac{1}{2}\right)\sum_{r=1}^{N}\sum_{t=1}^{T}\frac{(Inc_{rt} - \mu_r - Y_{rt-1}\delta)^2}{\sigma_{rt}^2} \tag{9}$$

Our objective is to maximize the above log-likelihood function (equation 9). The Solver can solve the simultaneous equations through the simulation process that estimates parameters by maximizing the above log-likelihood function. Once we estimate the parameters $\omega, \alpha, and\ \beta$, we obtain a $NT \times 1$ vector of conditional variance which will be used as the measure of income volatility in our main model.

Figure 3 depicts the average Income Volatility for US counties over 15 years from 2003 to 2017. The blue color counties fall among the top 20% of counties with high per capita personal income volatility (low Economic Stability) while counties with red colors belong to the group of the lowest income volatile counties (high economic stability).

Figure 3. County Income Volatility Map (Using the GARCH Process)



Note: Authors have created this map in GIS. The above map shows income volatility for US counties which is estimated using the GARCH model. 20% counties from 3079 counties fall within the volatility range of 0.0026 to 0.1198 and are marked as Blue color. Blue counties indicate high-income volatile regions. As the color moves from blue to red, income volatility declines. The red colors indicate regions with the least income volatility or greater economic stability.

Estimation

We estimate a total of six Panel Data Regression models to study the relationship between "industry diversity and economic stability", "industry diversity and the unemployment rate", and "industry diversity and per capita income". We would like to highlight that Income volatility indicates the measure of economic stability. Therefore, Income volatility, unemployment rate, and per capita personal income are three dependent variables, and industry diversity (Hachman Index or Herfindahl-Hirschman index) is the main explanatory variable in our models. A set of other control variables have also been used in these models. The Hausman test identifies that an Individual Fixed-effects Model is more appropriate than the Random-effects model (Baltagi, 2005). An Individual Fixed-effects model uses time-invariant dummy variables to capture individual-specific effects. Equation 10 to Equation 12 shows our models. We use either the Hachman or the Herfindahl-Hirschman index as the measure of diversity index for each of the following three equations.

$$IncVol_{rt} = \ddot{v}_r + DivIndx_{rt}\ddot{\partial} + X_{rt}\ddot{Y} + \ddot{\eta}_{rt} \tag{10}$$

$$UnemRate_{rt} = \bar{\bar{v}}_r + DivIndx_{rt}\bar{\bar{\partial}} + X_{rt}\bar{\bar{Y}} + \bar{\bar{\eta}}_{rt} \tag{11}$$

$$LPCI_{rt} = \check{v}_r + DivIndx_{rt}\check{\partial} + X_{rt}\check{Y} + \check{\eta}_{rt} \tag{12}$$

$IncVol_{rt}, UnemRate_{rt}, and\ LPCI_{rt},$ are column vectors of $NT \times 1$ matrix represents the Income Volatility, Unemployment Rate, Log Per Capita Income for region *r* in time *t*. $DivIndx_{rt}$ is also a column vector of $NT \times 1$ that takes the value of one of these two diversity indexes: the Hachman Index or the Herfindahl-Hirschman Index. v_r captures the individual effects for region r in the fixed effects model, which is a vector of $NT \times N$ matrix. $\eta_{it}$is a column vector of $NT \times 1$ matrix which is independent and identically distributed $IID \sim (0, \sigma^2)$. X_{rt} is the $NT \times k$ matrix of control variables, and Υ is the corresponding coefficients of control variables with a $k \times 1$ dimension. Control variables are taken based on existing literature, and the rest of these variables are assumed to have a significant impact on economic stability (Deller & Watson, 2016a, 2016b; Izraeli & Murphy, 2003; Malizia & Ke, 1993; Pallares & Adkisson, 2017; Wagner & Deller, 1998). However, we ignore variables that might cause the problem of multicollinearity. The following Table 1 provides the description of all variables and their sources.

Estimates from equations (10), (11), and (12), are not entirely unbiased estimations due to missing observations in the industry-level employment data. Industry employment data has been used to estimate Industry Diversity Indexes (Herfindahl-Hirschman Index and Hachman Index).

Table 1: Variable Description and Sources

Variable	Description	Source
Dependent Variables		
IncVol	Real Personal Income per Capita Volatility	1
UnemRate	Log Unemployment Rate	2
LPCI	Log Real Per Capita Personal Income	1
Independent Variables		
DivIndx	1. Herfindahl-Hirschman Diversity Index 2. Hachman Diversity Index	1
PCNFE	Per Capita Net Flow of Earnings to a county	1
LPCTrr	Log Per Capita Personal Transfer Receipt	1
LEST	Log Number of Establishments	2
LAWWage	Log Average Weekly Wage	2
LDens	Log Population Density	3
LPAge1864	Log Percentage of People Age Between 18 to 64	3
Lpop	Log Population	3
LEmp	Log Employment	2
Recession	Recession periods 2008, 2009, 2010	4
Metro	If population more or equal to 50,000 in a county	4
IntHachRec	Interaction between Hachman Diversity index and Recession	1
IntHerfRec	Interaction between Herfindahl Diversity index and Recession	1
IntHachMtr	Interaction between Hachman Diversity index and Metro	1
IntHerfMtr	Interaction between Herfindahl Diversity index and Metro	1
IMR	Inverse Mills Ratio	5

Notes: IncVola and DivIndx are the authors' own calculations. Recession and Metro are dummy variables.
Data sources:
1. Bureau of Economic Analysis: Regional economic accounts (retrieved from http://www.bea.gov).
2. Bureau of Labor Statistics (retrieved from http://www.bls.gov).
3. US Census Bureau: (retrieved from http://www.census.gov).
4. Dummy variable.
5. Authors' own estimation from a Probit Model.

It is necessary to use a correction method in our models to get unbiased estimations. Therefore, we propose performing the Heckman Selection Process to correct for biases in equation (10) to equation (12). The winner of the Nobel Memorial Prize in Economic Science, James Heckman, first introduced this technique to correct for non-randomly selected samples.

To conduct the Heckman Correction process, we will follow (Heckman, 1976, 1979). The first step of the two-step Heckman selection process begins with the following Equation (13). For simplicity, we consider only one single equation in Equation (13) out of the above three equations from Equation (10) to Equation (12).

$$Y_{1rt} = \dot{v}_r + Div_{rt}\dot{\partial} + X_{rt}\dot{\Upsilon} + \dot{\eta}_{rt} \tag{13}$$

Equation (13) is the main model in this process. Where, $Y_{rt}$is the dependent variable which could be *IncVol*, UnemRate, or LPCI. Div_{rt} is one of our two diversity indexes: the Herfindahl index or the Hachman index. X_{rt} is the $NT \times k$ matrix of control variables for region *r* at time *t*. η is the random error terms. In the Heckman Correction Process, we can write the regression function for the incomplete sample as:

$$\begin{aligned} &E(Y_{1rt}|X_{rt}, Div_{rt}, Sample\ Selection\ Rule) \\ &\qquad = \dot{v}_r + Div_{rt}\dot{\partial}_1 + X_{rt}\dot{Y}_1 + E(\dot{\eta}_{rt}|Sample\ Selection\ Rule) \end{aligned} \tag{14}$$

Since some data in Div_{it} are missing or cannot be observed, the expectation of $\dot{\eta}_{it}$ may not be zero and parameter $\dot{\partial}$ will be a biased estimate. Therefore, the Sample Selection Rule is when $E(Div_{1it}) \geq C$ and Div_{1it} can be considered as a truncated variable. The C is a constant value. When the employment of an industry in a region is below a certain number C, usually, they don't publish the number. Therefore, industry diversity cannot be measured for those regions. Thus, the equation (14) can be written as:

$$E(Y_{1rt}|X_{rt}, Div_{rt}, Div_{rt} \geq C) = \dot{v}_r + Div_{rt}\dot{\partial} + X_{rt}\dot{\Upsilon} + E(\dot{\eta}_{rt}|Div_{rt} \geq C) \tag{15}$$

The Heckman second step equation is a latent process where the dependent variable is censored based on observed and unobserved data.

$$Y_{2rt} = \acute{o}_r + Z_{rt}\text{Ч} + \vartheta_{rt} \tag{16}$$

Equation (16) is our Probit model in the Heckman selection process. Where ó is a constant, Z_{it} is a set of explanatory variables, ϑ_{it} is denoted as the random error term. Y_{2rt} is a binary variable which can be defined such that,

$$Y_{2rt} = \begin{cases} 1\ if\ Div_{rt} \neq NA \\ 0\ Otherwise \end{cases}$$

Since Div_{it} has some missing observations, we can consider Y_{1rt} data not to be usable in equation (13). Therefore, we can define our binary dependent variable Y_{2rt} in equation (16) in the following manner.

$$Y_{2rt} = \begin{cases} 1 \; if\ Stabl\ observations\ are\ usable \\ 0 \; Otherwise \end{cases}$$

It is clear that the expected value of Y_{2rt} depends on if Y_{2rt} value usable or in other words if $Y_{2rt} \geq 0$. Thus, equation (14) can be written as

$$E(Y_{1rt}|X_{rt}, Div_{rt}, Y_{2rt} \geq 0) = \dot{v}_r + Div_{rt}\dot{\partial} + X_{rt}\dot{Y} + E(\dot{\eta}_{rt}|\vartheta_{rt} \geq -\text{ó}_r - Z_{rt}\text{Ч}) \tag{17}$$

We assume that $\dot{\eta}_{rt}$ is independent of ϑ_{rt} and conditional mean of $\dot{\eta}_{rt}$ is zero. The distribution of $\vartheta_{rt} \sim$ N(0, 1). Since, $\vartheta_{rt} \geq -\text{ó}_r - Z_{rt}\text{Ч}$

$$\Pr(\vartheta_{rt} \geq -\text{ó}_r - Z_{rt}\text{Ч}) = 1 - \boldsymbol{\Phi}(-\text{ó}_r - Z_{rt}\text{Ч}) = \boldsymbol{\Phi}(\text{ó}_r + Z_{rt}\text{Ч}) \tag{18}$$

Now we can reform equation (17) as

$$E(Y_{1rt}|X_{rt}, Div_{rt}, Y_{2rt} \geq 0) = \dot{v}_r + Div_{rt}\dot{\partial} + X_{rt}\dot{Y} + \rho\sigma_{\dot{\eta}}\frac{\phi(\text{ó}_r + Z_{rt}\text{Ч})}{\boldsymbol{\Phi}(\text{ó}_r + Z_{rt}\text{Ч})} \tag{19}$$

ρ is the correlation between $\dot{\eta}$ and ϑ. σ is the standard deviation of the errors $\dot{\eta}$. $\phi(.)$ and $\boldsymbol{\Phi}(.)$ are the probability density function and Cumulative Distribution function respectively. We know that the Inverse Mills Ratio (λ) can be defined as

$$\lambda_{rt} = \frac{\phi(\text{ó} + Z_{it}\text{Ч})}{\boldsymbol{\Phi}(\text{ó} + Z_{it}\text{Ч})} \tag{20}$$

If ρ = 0 or no correlation between the $\dot{\eta}$ and ϑ, then the estimation should be unbiased. However, if we assume ρ > 0 and σ > 0, we need to apply the correction term. The Inverse Mills Ratio is the appropriate correction term in the Heckman two-step process. Therefore, we need to estimate the following equation.

$$Y_{1rt} = \dot{v}_r + Div_{rt}\dot{\partial} + X_{rt}\dot{\Upsilon} + \lambda_{rt}\text{Ƨ} + \dot{\eta}_{rt} \tag{21}$$

The distribution of $\dot{\eta}_{rt} \sim N(0, \sigma_{\dot{\eta}}^2)$, where λ_{rt} is the Inverse Mills Ratio and Ƨ is the parameter to be estimated. We can consider equation (21) to be the unbiased estimation of our model with the Heckman two-step correction process. If we replace Y with our three dependent variables like Equation (10), Equation (11), and Equation (12), we will get the following three equations.

$$IncVol_{rt} = \ddot{v}_r + DivIndx_{rt}\ddot{\partial} + X_{rt}\ddot{\Upsilon} + \lambda_{rt}\mathcal{Z} + \ddot{\eta}_{rt} \tag{22}$$

$$UnemRate_{rt} = \bar{\bar{v}}_r + DivIndx_{rt}\bar{\bar{\partial}} + X_{rt}\bar{\bar{\Upsilon}} + \lambda_{rt}\mathcal{Z} + \bar{\bar{\eta}}_{rt} \tag{23}$$

$$LPCI_{rt} = \check{v}_r + DivIndx_{rt}\check{\partial} + X_{rt}\check{\Upsilon} + \lambda_{rt}\mathcal{Z} + \check{\eta}_{rt} \tag{24}$$

From Equation (22) to Equation (24) are considered to be the unbiased estimators of individual fixed-effects models. Now we can observe the effects of diversity (Herfindahl index or Hachman index) on Economic stability, Unemployment rate, and Per capita income.

We have performed the following simple Probit model to get the Inverse Mills Ratio.

$$Bi_{rt} = C_{0_r} + \dot{\theta}_1 LPop_{rt} + \dot{\theta}_2 LEmp_{rt} + \dot{\vartheta}_{rt} \tag{25}$$

Bi is a binary variable of 0 and 1. Bi is 1 if the data is usable or 0 otherwise. log population and log employment have been used as our two explanatory variables denoted as $LPop\ and\ LEmp$ in Equation (25). $\dot{\theta}_1$ and $\dot{\theta}_2$ are parameters to be estimated. C_0 is the constant term, and ϑ is the random error term.

Results

Table 2 presents the descriptive statistics. The highest value, lowest value, mean, and standard deviation are provided in the table. Variables such as Recession, Metro, and their interaction with industry diversity indexes are important for this research. Finally, we can observe from Table 2 that the Coefficient of Variation is much higher for the Herfindahl-Hirschman index than the Hachman Index, which are 27.79% and 23.27%, respectively. This tells us the Herfindahl-Hirschman index varies more from the mean value than the Hachman index. However, the range of the Herfindahl-Hirschman Index is lesser than the Hachman Index. The range of the Herfindahl-Hirschman index is 0.36, and the Hachman index is 0.91.

We perform a total of six individual fixed effects models with the Heckman Correction to get an unbiased estimation. We present summary results for Individual Fixed Effects models with the Heckman correction in Table 3 from Model 1 to Model 6. Summary results only provide estimates of some key explanatory factors, which we estimated from equations (22), (23), and (24). Full results table that includes estimates of all variables is provided in Appendix Table (B).[2] We estimate Inverse Mills Ratio (IMR) from the Probit model[3] in equation (25).

[2] See Appendix for results (Table B).

[3] See Appendix for results (Table A).

Table 2. Descriptive Statistics of the Variables

	Highest	Lowest	Mean	St.Dev	Coef. of Var. (x 100)
IncVola	0.124016	8.94E-05	0.00283	0.006686	236.2175382
UnemRate	3.363842	0.09531	1.776363	0.411028	23.13875368
LPCI	12.45022	9.545952	10.52289	0.260972	2.480042481
HachIndx	0.976248	0.069711	0.74826	0.174124	23.27055032
HerfIndx	0.428736	0.066781	0.095677	0.026594	27.79589547
PCNFE	39.98141	-269.761	2.271483	8.473589	373.0421014
LPCTrr	9.801012	7.144407	8.880146	0.309448	3.484712918
LURate	3.363842	0.09531	1.776363	0.411028	23.13875368
LEST	13.08407	2.302585	6.614826	1.417036	21.4221238
LAWWage	7.798523	5.693732	6.453094	0.230174	3.56687094
LDens	11.1971	-2.8168	3.767402	1.695482	45.00400663
LPAge1864	4.374699	3.580754	4.096805	0.061448	1.499909083
Recession	1	0	0.2	0.400004	200.0021652
IntHachRec	0.976209	0	0.060763	0.210821	346.9541161
IntHerfRec	0.406144	0	0.007735	0.027197	351.6043861
Metro	1	0	0.310209	0.462584	149.1201477
IntHachMtr	0.976248	0	0.223037	0.367505	164.7733634
IntHerfMtr	0.428736	0	0.025912	0.044099	170.1864868
IMR	3.310228	0.003112	0.868353	0.22168	25.52882867

Note: Mean and Standard deviation of the above variables are estimated from the data for 3079 counties over 15 years from 2003 to 2017. A description of these variables is provided in Table 1.

Statistically significant estimates of IMR confirm that the selection parameter is appropriate for these models. Finally, the Hausman test[4] results suggest that the Individual Fixed Effects model is better than the Random Effects model.

Table 3 results suggest that the Income Volatility is expected to reduce by 0.0025 percent on average with a 10 units increase in the Hachman diversity index. Greater industry diversity leads to low-Income volatility which indicates greater Economic Stability in a region. The result also shows that Hachman diversity has a bigger impact on reducing the unemployment rate. A

[4] See Appendix for results (Table C).

one percentage point increase in the Hachman diversity index expects to reduce 0.37 percent of the unemployment rate in a US county. We can make the same conclusion for the Herfindahl-Hirschman diversity index in Model 4. Per unit of additional Herfindahl diversity can cause a 4.37 percent lower unemployment rate. However, the Herfindahl-Hirschman index is more sensitive than the Hachman index in predicting the unemployment rate. However, we find that industry diversity has a significant negative relationship with the per capita income in Model 5. A 0.03 percent reduction in income per capita is expected with 1 unit of additional industry diversity. From the above results we can infer that for achieving long-term economic stability, industry diversity is important for the US while that might reduce the overall income per capita. Therefore, counties facing a vulnerable economy and loss of employment can aim to achieve a more stable economy by promoting the industry diversity.

It will be interesting to see if a county can hold its economic stability during a recession and whether industry diversity is really effective in achieving greater stability during an economic recession. We consider the years 2008, 2009, and 2010 as recession periods in the United States. Except for Model 2, all other models in Table 3 show recession has a positive relationship with Income Volatility and Unemployment Rate. We can expect a 0.0021 percent increase in Income Volatility (lower economic stability) on average during the recession period. Model 3 and Model 4 show a 6.55 percent and 18.71 percent increase in the Unemployment Rate due to a recession. The results also suggest that recession also reduces the income per capita by 1.58 percent (Model 5) and 3.54 percent (Model 6). From our estimates, we have strong evidence to claim that recession hurts all three economic variables, economic stability, employment, and per capita income.

Most importantly, the interaction between the Hachman index and recession shows a negative relationship with Income Volatility (Model 1). It suggests that income volatility will be lower during the time of a recession if a county achieves a higher level of industrial diversity. However, unexpectedly interaction between the Hachman index and recession in Model 3 shows a positive relationship with the unemployment rate. The possible explanation for this situation could be: that during a recession many people moved to the urban core to search for employment where industry diversity is comparatively higher than in other regions ((Johnson et al., 2016). This will possibly lead to a higher level of unemployment in that county. Model 5 and Model 6 show that per capita income will reduce by 0.02 percent and 0.06 percent respectively during the time of a recession even achieving a percentage point higher industrial diversity in a region.

Table 3. Fixed-Effects Models with the Heckman Correction Selected Variables

Models	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Variables	**IncVola**	**IncVola**	**UnemRate**	**UnemRate**	**LPCI**	**LPCI**
HachIndx	-0.00025*** (0.000018)		-0.3745*** (0.0678)		-0.0322** (0.0140)	
HerfIndx		-0.000031 (0.00011)		4.2763*** (0.4052)		0.0262 (0.0843)
Recession	0.00002*** (0.000004)	-0.000003 (0.000004)	0.0634*** (0.0165)	0.1715*** (0.0137)	-0.0159*** (0.0034)	-0.0361*** (0.0029)
Metro	-0.00017*** (0.000015)	0.000079*** (0.000012)	0.0728 (0.0555)	-0.1268*** (0.0456)	-0.0482*** (0.0115)	-0.0597*** (0.0095)
IntHachRec	-0.000025*** (0.0000056)		0.1427*** (0.0213)		-0.0191*** (0.0044)	
IntHerfRec		0.000042 (0.000037)		-0.0386 (0.1369)		0.0597** (0.0286)
IntHachMtr	0.000287*** (0.000021)		-0.0605 (0.0768)		0.0426*** (0.0160)	
IntHerfMtr		-0.00048*** (0.000112)		1.6051*** (0.4147)		0.4022*** (0.0867)
IMR	0.00026*** (0.00002)	0.00024*** (0.000021)	4.7068*** (0.0784)	4.7472*** (0.0772)	-0.3932*** (0.0163)	-0.3951*** (0.0162)
R^2	0.22185	0.21099	0.49323	0.49767	0.91653	0.91659
MSE	2.88546E-09	2.92573E-09	0.0404	0.04008	0.00175	0.00175

Note: ***/**/* indicates level of significance at 0.01, 0.05, and 0.10 respectively. Standard errors are in the parenthesis. Models are estimated using the Heckman Correction process to avoid biases due to missing observations in the county industry-level data.
1. This table includes only the focus variables. To get full results, please see Table B in the Appendix which includes all other control variables.
N = The sample includes 3079 counties and
T = From Year 2003 to 2017.

The interaction of recession and diversity impact on per capita income loss is lower than a simple diversity impact. That implies greater industrial diversity is more effective while the nation facing a recession.

Another key objective is to observe whether our dependent variables vary between metro and non-metro counties. We consider counties with populations equal to or greater than fifty thousand as metro Counties. Our result suggests a metro county is more economically stable and has a low unemployment rate compared to a non-metro county. If we look at the industry diversity and metro interaction effect we see that additional industrial diversity in a non-metro county is more effective than in a metro county for achieving greater economic stability. A positive coefficient of 0.00028 (Model 1) and a negative coefficient of 0.00048 (Model 2) imply that additional diversity has a lower impact on reducing the economic volatility in a metro county as compared to a non-metro county. However, metro counties outperform non-metro counties while estimating the unemployment rate. One additional percentage point higher diversity in a metro county shows a 1.62 percent lower unemployment rate (Model 4). Finally, the interaction between Industry Diversity and Metro has an ambiguous impact on per capita income. It shows a positive relationship for both the diversity indexes. For consistency, it is important to have opposite signs for the Hachman index and the Herfindahl-Hirschman index.

Conclusion

This paper uses the GARCH model for panel data for estimating income volatility. To the best of our knowledge, no scholar of regional science ever performed GARCH to measure economic stability before. This methodology allows us to generate annual volatility estimates by county. Thus, we are able to investigate the dynamic interaction between changes in volatility (economic stability) over time and industry diversity. We utilize data on 3079 US counties over 15 years to analyze this dynamic relationship between industry diversity and economic stability.

We overcome the issue of missing data at the county level by using the Heckman correction. This allows us to estimate an unbiased fixed-effects model. We find that a region with high industrial diversity has lower economic volatility and unemployment rate. We also observe that the impact of an economic recession is comparatively low in an industrially diversified region than in a non-diversified region. However, a diversified region may face a higher unemployment rate during the recession. A further finding is that Metro counties are more diversified than non-metro counties; yet, the non-metro county can achieve greater economic stability through industry diversity than a metro county. That is, the benefits of diversification are greater in rural than urban areas while the target is to achieve stable income.

Finally, this paper distinguishes between economic growth and economic stability. Economic growth is measured as the per capita income growth, while economic stability is measured as the per capita income volatility. Unlike the other regional economists, we find diversity has a negative correlation with the per capita income. Specialization in one or a few industries can be more effective in case of achieving high per capita income. However, we cannot completely ignore the importance of industry diversification. Diversity can be very effective in minimizing the loss of per capita income when the nation is hit by a recession. Therefore, a region can achieve economic growth along with economic stability through industry diversification. Based on the outcome of this paper, we cannot suggest a tradeoff between economic stability and economic growth when a region wants to diversify its economy.

Appendix

Table A. Probit Result

Probit binary choice model/Maximum Likelihood estimation
Log-Likelihood: -14896.73
Model: Y == '1' in contrary to '0'
(df = 46182)
Estimates:

	Estimate	Std. error	t value	Pr(>t)
(Intercept)	-13.366908	0.117165	-114.086	< 2.2e-16 ***
Lpop	0.676756	0.021331	31.727	< 2.2e-16 ***
LEmp	0.629602	0.019625	32.081	< 2.2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Significance test:
chi2(2) = 32431.34 (p=0)

Note: ***/**/* indicates level of significance at 0.01, 0.05, and 0.10 respectively. The first step of the Heckman Correction process is to estimate a Probit Model. We use R programming software to run the Probit Model. After performing the Probit model, we are able to estimate the Inverse Mills Ratio (IMR), which is the second step of the Heckman Correction process. IMR will be used as the correction factor in our main model.

Table B. Fixed-Effects Models with the Heckman Correction showing all regressors

Models	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Variables	**IncVola**	**IncVola**	**UnemRate**	**UnemRate**	**LPCI**	**LPCI**
HachIndx	-0.00025*** (0.000018)		-0.3745*** (0.0678)		-0.0322** (0.0140)	
HerfIndx		-0.000031 (0.00011)		4.2763*** (0.4052)		0.0262 (0.0843)
Recession	0.00002*** (0.000004)	-0.000003 (0.000004)	0.0634*** (0.0165)	0.1715*** (0.0137)	-0.0159*** (0.0034)	-0.0361*** (0.0029)
PCNFE	0.000002*** (0.00000034)	0.000002*** (0.0000003)	-0.0229*** (0.0013)	-0.0208*** (0.0013)	0.0094*** (0.00026)	0.0096*** (0.00026)
LPCTrr	0.00005*** (0.000005)	0.000039*** (0.000005)	0.8646*** (0.0186)	0.8885*** (0.0185)	0.1895*** (0.0039)	0.1905*** (0.0039)
LEST	0.000064*** (0.0000093)	0.000051*** (0.000009)	0.2141*** (0.0383)	0.2328*** (0.0379)	0.1619*** (0.0072)	0.1637*** (0.0072)
LAWWage	-0.00031*** (0.00001)	-0.00028*** (0.00001)	-1.066*** (0.037)	-1.0129*** (0.0364)	0.8315*** (0.0077)	0.8339*** (0.0074)
LDens	-0.000034** (0.000013)	-0.000047*** (0.000013)	-0.2095*** (0.0474)	-0.2679*** (0.0475)	-0.3447*** (0.0105)	-0.3469*** (0.0105)
LPAge1864	-0.000094*** (0.000032)	-0.00007** (0.000033)	5.2338*** (0.123)	5.2325*** (0.1223)	-0.0532** (0.0256)	-0.0518** (0.0256)
Metro	-0.00017*** (0.000015)	0.000079*** (0.000012)	0.0728 (0.0555)	-0.1268*** (0.0456)	-0.0482*** (0.0115)	-0.0597*** (0.0095)
IntHachRec	-0.000025*** (0.0000056)		0.1427*** (0.0213)		-0.0191*** (0.0044)	
IntHerfRec		0.000042 (0.000037)		-0.0386 (0.1369)		0.0597** (0.0286)
IntHachMtr	0.000287*** (0.000021)		-0.0605 (0.0768)		0.0426*** (0.0160)	

IntHerfMtr		-0.00048*** (0.000112)		1.6051*** (0.4147)		0.4022*** (0.0867)
IMR	0.00026*** (0.00002)	0.00024*** (0.000021)	4.7068*** (0.0784)	4.7472*** (0.0772)	-0.3932*** (0.0163)	-0.3951*** (0.0162)
R^2	0.22185	0.21099	0.49323	0.49767	0.91653	0.91659
MSE	2.88546E-09	2.92573E-09	0.0404	0.04008	0.00175	0.00175

Note: ***/**/* indicates level of significance at 0.01, 0.05, and 0.10 respectively. Standard errors are in the parenthesis. Models are estimated using the Heckman Correction process to avoid biases due to missing observation in the county industry-level data. This table provides estimates for all variables that have been used in these models.
N = The sample includes 3079 counties and
T = From Year 2003 to 2017.

Table C. Hausman Test Results

Model 1
Hausman Test
Ho: random effect model is appropriate.
data: IncVolaF ~ HachIndx + PCNFE + LPCTrr + LEST + LAWWage + LDens + ...
chisq = 55.67, df = 12, p-value = 1.372e-07

Model 2
Hausman Test
Ho: random effect model is appropriate.
data: IncVolaF ~ HerfIndx + PCNFE + LPCTrr + LEST + LAWWage + LDens + ...
chisq = 55.56, df = 12, p-value = 1.436e-07

Model 3
Hausman Test
Ho: random effect model is appropriate.
data: LURate ~ HachIndx + PCNFE + LPCTrr + LEST + LAWWage + LDens + ...
chisq = 5858.7, df = 12, p-value < 2.2e-16

Model 4
Hausman Test
Ho: random effect model is appropriate.
data: LURate ~ HerfIndx + PCNFE + LPCTrr + LEST + LAWWage + LDens + ...
chisq = 6239.3, df = 12, p-value < 2.2e-16

Model 5
Hausman Test
Ho: random effect model is appropriate.
data: LPCI ~ HachIndx + PCNFE + LPCTrr + LEST + LAWWage + LDens + LPAge1864 + ...
chisq = 1013.2, df = 12, p-value < 2.2e-16

Model 6
Hausman Test
Ho: random effect model is appropriate.
data: LPCI ~ HerfIndx + PCNFE + LPCTrr + LEST + LAWWage + LDens + LPAge1864 + ...
chisq = 1278.6, df = 12, p-value < 2.2e-16

Note: We perform the Hausman test to see whether a Fixed-Effects or a Random-Effects model is more appropriate for our dataset. The null hypothesis in R programming software assumes that the Random-Effects model is appropriate by default. Hausman test of results of all our models rejects the null hypothesis.

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