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Interpreting Economic Diversity as the Presence of Multiple Specializations

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Abstract

Conventional wisdom indicates that economic specialization can promote economic growth, whereas economic stability is theoretically associated with diversified economies. This conflicting relationship between specialization and diversity has been questioned, as regional scientists have suggested that specialization and diversity can coexist in a regional economy and proposed the concept of diversified specializations. To test this proposition empirically, three Herfindahl Hirschman Indices measuring regional economic diversity were used to examine the relationship between economic structure and regional economic performance among 359 metropolitan statistical areas (MSA) in the contiguous U.S. The first index measures economic diversity across 87 three-digit North American Industry Classification Systems (NAICS) sectors for each MSA; the second index quantifies economic diversity among 51 clusters identified by Delgado et al. in *J. Econ. Geogr.* 16(1), 1-38 (2016); and the third index considers the effects of both industry and cluster diversity. This analysis confirms that industry diversity promotes economic stability and also demonstrates that cluster diversity contributes to both economic stability and growth. I thus conclude that regions can simultaneously pursue both high and stable economic growth.

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1 Introduction

Economic structure is often understood through economic specialization and diversity constructs where economic diversity is defined as, "the variety of economic activity which reflects differences in economic structure at a specific time" (Malizia and Ke, 1993, p. 222). Most regional economies—such as Pittsburgh and New York in Chinitz's (1961) description—lie on a continuum between pure specialization[1] and complete diversity. In contrast, it is traditionally assumed that economic clustering and diversity are mutually exclusive (Deller and Watson, 2016; Wagner, 2000; Wagner and Deller, 1998). This assumption of mutual exclusivity becomes more apparent in the examination of economic diversity measures, such as the Herfindahl Hirschman Index (HHI), where economic diversity is measured as the sum of the squared regional shares of employment for each industry (e.g. Chiang, 2009; Hong and Xiao, 2016; Trendle, 2006; Wagner, 2000). In this commonly used metric, higher values for the HHI indicate greater economic specialization or conversely, lower diversity.

However, the dichotomy of economic specialization and diversity has been challenged as regional scientists have reconsidered the definition of economic diversity as the presence of, rather than the absence of, specialization to stress that regional economic systems can be specialized and diversified simultaneously (Desrochers and Sautet, 2008; Dissart, 2003; Hong and Xiao, 2016; Jackson, 2015; Malizia and Ke, 1993; Wagner and Deller, 1998). Nevertheless, with the exception of Hong and Xiao (2016), these authors have only established the basic conceptual framework of diversified specializations but have not applied this framework to empirical studies. Specifically, Hong and Xiao (2016) proposed a Multiple Specialization Index (MSI) that allows for the measurement of multiple specializations in economic activities. In Hong and Xiao's study, the MSI is calculated as the ratio of the number of specialized industries to the number of non-zero employment industries in the region. In addition to those, specialized industries have a location quotient (LQ) value greater than a specified cut-off value. However, as suggested by Porter (2003), Spencer et al. (2010), and Delgado et al. (2016), not all industries are specialized. For example, drug stores and elementary schools only serve a local market and should not be considered as candidates for economic specializations.

[1]The terms of "cluster" and "specialization" are used interchangeably in this paper even though specialized establishments may not be spatially clustered.

To address this issue, this paper develops an alternative measure of economic structure that enables the interpretation of diversified specializations for empirical analysis. As economic specialization can contribute to regional economic growth, and a diverse regional economy is theoretically associated with stable regional economic growth, this measure can leverage the benefits of specialization and diversity concurrently. This paper also provides an overview of the relationship between economic specialization and diversity within current economic structure measures, including the HHI and Hong and Xiao's (2016) MSI. In addition, policy implications are offered when economic development strategies shift from pure specialization and complete diversification to developing diversified specializations.

Accordingly, Section 2 of this paper provides a theoretical background on economic specialization and diversity. Methodology is described in Section 3, followed by the results and discussion. The final section concludes with the findings of this paper.

2 Background

2.1 Economic structure and regional economic performance

There is a general consensus among regional scientists that a diverse economy is associated with stable economic performance, because the economy is not dependent on only a few industries and might suffer less from external economic downturns as suggested by Chinitz (1961) and Conroy (1975), for example. When comparing the economic agglomerations of New York and Pittsburgh in the early 1960s, Chinitz (1961, p. 281) found that "diversified areas exhibit more stability in their growth because their fortunes are not tied to the fortunes of a few industries." Similarly, Conroy (1975) borrowed the concept of portfolio from the finance literature to explain the diversity-stability relationship. He reasons that, for a given region, every industry can be seen as an independent investment, and a collection of all regional industries can be seen to be an industry portfolio. Accordingly, portfolio risk is greater for a regional economy that has invested in only a few industries.

By contrast, the relationship between regional economic structure and economic growth can be explained by two competing theoretical perspectives. On the one hand, conventional wisdom and much of the previous literature, such as the Marshall-Arrow-Romer (MAR) model and Porter

(1990, 1998), hold that intra-industry specialization is preferred for economic growth. As originally proposed by Marshall (1890), Arrow (1962) and Romer (1986), and later formalized by Glaeser et al. (1992), the MAR model hypothesizes that knowledge spillovers tend to be industry specific and that concentrations of similar industries facilitate growth. These knowledge spillovers are known as MAR externalities. As with MAR, Porter (1990, 1998) has suggested that specialization can promote economic growth, but his concept of clusters was developed from the perspective of competitiveness. On the other hand, Jacobs (1969) suggested that diversity is more conducive to economic growth than specialization. Specifically, knowledge spillovers can arise among diverse firms and economic agents, and thus stimulate innovation and growth; these spillovers are referred to as Jacobs' externalities.

2.2 Specialization and diversity: two sides of the same coin?

When it comes to the relationship between specialization and diversity, the traditional view holds that diversity can be interpreted as the absence of specialization; in other words, specialization and diversity are two sides of the same coin. In relation to regional economic performance, regions have to choose between a stable yet slow growth and a high yet risky growth. The traditional view, however, has been challenged by Malizia and Ke (1993), Wagner and Deller (1998), and others. Malizia and Ke (1993) were among the first researchers to consider their coexistence. In their words, "these specializations can be the source of competitiveness as well as compensate for one another when business cycles or external shocks occur" (Malizia and Ke, 1993, p. 223). Despite their conceptual advances, Malizia and Ke (1993) still acknowledged that a trade-off exists between growth and instability. In contrast, Wagner and Deller (1998) suggested that short-term economic development strategies can focus on specialization to promote growth, while long-term policy can aim at stability through diversification, indicating that the trade-off between stability and growth no longer exists.

However, the concept of diversified specializations has not been widely applied to measures of economic structure, like the national average, the ogive, the entropy and the Herfindahl-Hirschman Index (HHI) for empirical analysis[2]. Among these measures, the HHI and the entropy measures have been used more extensively than others in empirical studies. This preference

[2] For comparative reviews of these structure measures, see Jackson (1984, 2015), Wagner (2000) and Dissart (2003)

is not only because of computational ease and limited data requirements, as suggested by Wagner (2000), Trendle (2006) and Jackson (2015), but also because the traditional view of the specialization-diversity dichotomy is embedded in these two measures. The HHI ranges from $1/N$ for a perfectly diversied economy to 1 if all employment is concentrated in one industry. Similarly, the entropy index reaches its maximum for a one-industry economy, whereas for its minimum, all employment is evenly distributed across sectors. By comparison, other structure measures, such as durable goods percentage and location quotient, decouple economic specialization and diversity; that is to say, unlike the entropy and HHI measures, one cannot simultaneously determine the levels of economic specialization and diversity.

As noted earlier, the only metric that addresses the coexistence of specialization and diversity is Hong and Xiao's (2016) Multiple Specialization Index, which is calculated as:

$$MSI_i = \frac{\sum_{n=1}^{N} SP_n}{N} \tag{1}$$

where N is the number of sectors in region i, n is the sector index; and SP_n equals 1 if the location quotient of sector n is greater than the cut-off value; otherwise, it equals 0. The cut-off value was set as the 80^{th} percentile LQ values for each three-digit NAICS (North American Industry Classification Systems) sector, and sectors with large LQs were identified as specializations. The MSI approaches a value of 1 for highly specialized economies and 0 if no sector is specialized. In essence, this index measures the number of specialized industries in a regional economy but is divorced conceptually from any notions of competitiveness, co-location, or interindustry linkages as suggested by Porter (1990, 1998). As such, the remainder of this section visits criteria to identify economic clusters for empirical analysis.

2.3 Identifying economic clusters

In Hong and Xiao's (2016) study, the MSI considers industries with non-zero employment as potential economic specializations, whereas, in reality, it is not meaningful to treat sectors that only serve local demand as candidates for economic clusters. As such, the definition of economic clusters is open to discussion. Originally, Porter (1998, p. 226) defined economic clusters as, "a form of network that occurs within a geographical location, in which the proximity of firms and institutions ensures certain forms of commonality and increases the frequency and impact of interactions." This definition might be useful for case studies of economic clusters such as Silicon Valley and Route 126 outside of Boston, but it appears to provide little operational guidance on measuring regional economic clusters for empirical analysis because of its ambiguity (Martin and Sunley, 2003; Yu and Jackson, 2011). As such, a more formal and operational definition of economic clusters is required.

Developing such a definition, of course, is a common step in quantitative analysis on economic clusters. For example, Porter (2003) classified all industries into three categories:

- *traded industries* that sell goods and services across regions and to other countries;
- *resource-based industries* that are located where the needed resources are found; and
- *local industries* that are industries present in most areas and sell locally.

In this classification, Porter (2003) argued that only traded industries can be economic clusters, although Spencer et al. (2010) suggested that resource-based industries can also be economically specialized. Methodologically, Porter (2003) identified economic clusters based on the geographical correlation of employment between traded industries. In Porter's (2003, p. 562) words, "if computer hardware employment is nearly always associated geographically with software employment, this provides a strong indication of locational linkages." The result of Porter's (2003) method is 29 traded clusters identified in the U.S. More recently, Delgado et al. (2016) extended Porter's (2003) method by considering co-location patterns of employment and establishments, input-output linkages, and similarity in labor occupation. As a result, they identified 51 traded clusters in the U.S. context, and each cluster is composed of several six-digit NAICS sectors. Additionally, based on Spencer et al. (2010), resource-based industries like coal mining can also be economic clusters in Delgado et al.'s (2016) result.

3 Methodology

3.1 Empirical frameworks

To study the effects of economic structure on short-term employment growth and long-term stability among 359 metropolitan statistical areas (MSAs) in the contiguous U.S., MSAs are used as the basic analytical units because they meaningfully constitute functional economic systems (Jackson, 1984; Malizia and Ke, 1993; Trendle, 2006). The following empirical models are used:

$$REI_i = f(DIV_i, CONTROL_i) \tag{2}$$

$$GROWTH_i = g(DIV_i, CONTROL_i) \tag{3}$$

where the dependent variables are economic performance indicators, including regional economic instability index (REI) and employment growth rate; and the independent variables are diversity measures and a set of control variables. In both Equations (2) and (3), the independent variables reveal the state of the regional economy in 2000, while the dependent variables capture short- (2000-2002) and long-term (2000-2014) changes in regional economic performance. All the variables used in this analysis are summarized in Table 1.

3.2 Economic performance indicators

Previous research assesses economic performance through many measures like growth rates of per capita income (Izraeli and Murphy, 2003; Wagner and Deller, 1998), unemployment rate (Attaran, 1986; Chiang, 2009; Mizuno et al., 2006; Watson and Deller, 2017), and employment instability index (Conroy, 1975; Jackson, 1984; Kort, 1981). Rather than adopt these measures, however, this analysis uses short-term employment growth and long-term regional economic instability as indicators of economic performance. This is not only because of their popularity in previous literature (Kort, 1981; Malizia and Ke, 1993; Trendle, 2006) and economic development policy discussion (Deller and Watson, 2016; Wagner and Deller, 1998), but also because they leverage the benefits of economic specialization and diversity at the same time.

Based on Malizia and Ke (1993), regional economic instability (REI) is calculated as:

$$REI_i = \Big\{ \sum_{i=1}^{N} [(E_{it} - E_{it}^{Tr}) \times 100 / E_{it}^{Tr}]^2 / T \Big\}^{1/2} \tag{4}$$

where i denotes the region index; E_{it} is the actual number of workers for region i at time t; T is the number of observed time spans; and E_{it}^{Tr} is the predicted number of workers for region i at time t using a linear trend

Table 1: Description of all the variables

Category	Symbol	Description	Data Source
Dependent Variable	REI	Economic instability, 2000-2014	BEA
	GROWTH	Employment growth rate, 2000-2002	BEA
Independent Variable	HHIS	HHI of 3-digit NAICS sectors, 2000	CBP
	HHIC	HHI of specialized clusters, 2000	CBP
	MHHI	MHHI=(1+HHIS)×(1+HHIC)	CBP
Control Variables	POP	Logged population size, 2000	Census
	EDU	Percentage of the population over 25 with at least a bachelor degree, 2000	Census
	NONWHITE	Percentage of the population non-white, 2000	Census
	INCOME	Per capita income relative to U.S. average, 2000	BEA
	GOODS	Percentage of employment in goods production industries (minus agriculture), 2000	BLS

Notes: CBP = County Business Patterns; BEA = Bureau of Economic Analysis; BLS = Bureau of Labor Statistics; NAICS = North American Industry Classification Systems; HHI = Herfindahl Hirschman Index

line. REI is measured using employment data from the Bureau of Economic Analysis (BEA) during the long-run study period from 2000 to 2014.

Employment growth rate for region i at time t is calculated as the percent rate of increase in total employment from $t-1$ to t.

$$GROWTH_i = \frac{(E_{it} - E_{it-1}) \times 100}{E_{it-1}} \tag{5}$$

where E_{it} is the actual number of workers for region i at time t and E_{it-1} is the number of workers at time $t-1$. Like REI, the growth variable is also calculated based on the BEA data sets but for the short term studying period from 2000 to 2002.

3.3 Measuring economic diversity

Similar to Jackson (1984), Malizia and Ke (1993) and Hong and Xiao (2016), the diversity variable is measured based on data from County Business Patterns (CBP). CBP is published annually by the U.S. Census Bureau and contains employment by the two to six-digit NAICS sectors for different levels of geographical regions like states, counties and zip-code areas. For confidentiality reasons, the U.S. Census Bureau uses data ranges for the number of employment for some sectors. Values to replace these ranges, however, were estimated in the Upjohn Institute's "WholeData" version of CBP, derived using Isserman and Westervelt's (2006) method. The complete data of 2000 were accessed and used to assess regional economic diversity.

Three HHI-based diversity measures of economic activities are used. The first measure quantifies the level of employment dispersion between 87 three-digit NAICS sectors and is the traditional measure of economic diversity used in Chiang (2009), Mizuno et al. (2006) and others. The HHI of sectors (HHIS) are defined as:

$$HHIS_i = \sum_{j=1}^{N} (e_{ij}/e_i)^2 \tag{6}$$

where e_{ij} is the employment of industry j in region i; E_i is the total number of people employed in the i^{th} region; and N stands for the number of industries. In Equation (6), the value of HHIS is between $1/N$ and 1. Smaller values of the index suggest greater dispersion or diversity in economic activities (i.e., employment).

To interpret economic diversity as the presence of multiple specializations, the second measure of economic diversity, based on Delgado et al. (2016)[3], revises the commonly used HHI in Equation (6) as follows:

$$HHIC_i = \sum_{j=1}^{M} (e_{ij}/e_i)^2 \tag{7}$$

where e_{ij} denotes the employment of cluster j in MSA i; E_i is the total employment of traded industries; and M is the number of clusters in the

[3] Purdue Center for Regional Development (2007) also developed a cluster template for regional analysis, but the emphasis of this template is mainly for rural regions; for example, compared to Porter (2003) and Delgado et al. (2016), jewelry clusters were excluded

same region. Similarly, the HHI of clusters[4] or HHIC ranges from $1/M$ to 1, and smaller values of this index suggest a greater level of diversity within clusters. Unlike the first diversity measure (i.e., HHIS), and Hong and Xiao's (2016) MSI, this measure of economic diversity is calculated using cluster definitions identified by Delgado et al. (2016) and also excludes the impact of local industries. These clusters also should be concentrated relative to the nation; that is to say, the LQ of these clusters are greater than 1[5]. The LQ for cluster j in region i is defined as:

$$LQ_{ij} = \frac{e_{ij}/E_i}{e_{Nj}/E_N} \tag{8}$$

where e_{ij} stands for employment for cluster j in region i; E_i is the total employment of traded industries in region i; e_{Nj} represents the national total employment of cluster j; and E_N is the total employment of traded industries for the whole study region. For a given cluster, an LQ greater than 1 indicates that the region has a higher concentration than the nation.

The mean of HHIS for U.S. MSAs is 0.049 (range, 0.030 to 0.179), while the mean of HHIC is 0.140 (range, 0.043 to 0.680). Figures 1 and 2 present the geographical distributions of industry and cluster diversity, where MSAs with greater than the average diversity values are differentiated from those with less than average diversity values. Comparing these two figures, 182 of the 359 MSAs in this analysis have high levels of both industry and cluster diversity, while 92 MSAs have low levels of industry and cluster diversity. In contrast, 49 MSAs are industrially diversified with limited cluster diversity, whereas 36 MSAs have strong cluster diversity but with low levels of industrial diversity. In addition, unlike Chinitz's (1961) observation mentioned earlier, New York City and Pittsburgh nowadays display high levels of both industry and cluster diversity.

To further assess the relationship between industry and cluster diversity, Figure 3 displays the scatterplot of the HHIC and the HHIS with the fitted linear trend line. As reflected by the R^2 value, the industry diversity measure only explains 36.7% of variation in the diversity index of clusters.

[4] Slaper et al. (2018) also developed an empirical measure of cluster diversity but did not emphasize the coexistence of specialization and diversity.

[5] The cut-off value of 1 has been criticized by numerous scholars (e.g. Carroll et al., 2008; Ellison and Glaeser, 1997; Tian, 2013). Future research might consider other cut-off values or the revised versions of LQ.

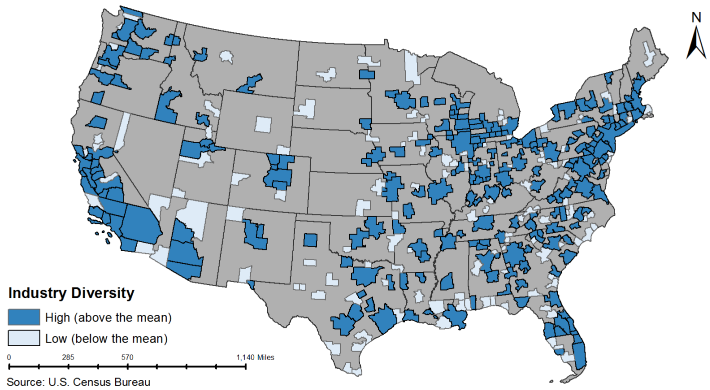

Figure 1: Industry diversity in the contiguous U.S.

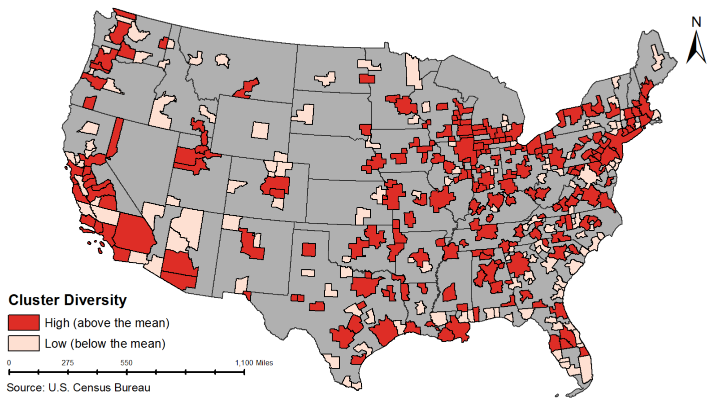

Figure 2: Cluster diversity in the contiguous U.S.

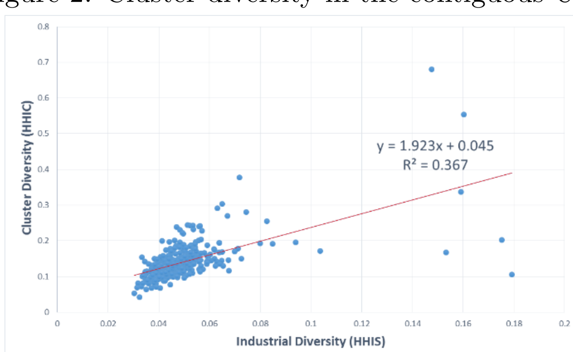

Figure 3: Correlation between industry and cluster diversity.

This weak correlation is understandable, as a higher degree of industry diversity might not necessarily display greater diversity within clusters.

Third, to consider the joint effect of both HHIC and HHIS, a multiplicative HHI (MHHI) is defined as:

$$MHHI_i = (1 + HHIC_i) \times (1 + HHIS_i) \tag{9}$$

where HHIS measures the economic diversity of sectors; and HHIC quantifies the diversity of economic clusters for a given region. Ideally, if the base economy is most diversified at both sector and cluster levels, then MHHI reaches its minimum; conversely, if the economy has a single industry that forms only one cluster, the value of MHHI is 4.

3.4 Modeling methods

As suggested and confirmed by Trendle (2006), Deller and Watson (2016), and others, spatial dependence does exist in the way in which economic structure itself impacts regional economic performance, whereas the ordinary least squares (OLS) model would ignore this dependence and thus result in inaccurate estimates. The spatial Durbin model (SDM) is such an approach that incorporates spatial dependence in both dependent and independent variables when compared to the spatial autoregressive model and the spatial error model. Moreover, LeSage and Pace (2009) suggested that the SDM should be used when one believes that there might exist omitted variables that demonstrate spatial autocorrelation.

The SDM can be described as:

$$y = \rho W y + X\beta + WX\gamma + \varepsilon \tag{10}$$

where y is the dependent variable for region $i(i = 1, , N)$, X is a matrix of independent variables; β is a vector of estimated coefficients of the independent variable; ρ is a coefficient that describes the strength of the spatial autocorrelation in the dependent variable; γ[6] is a vector of estimated coefficients of the spatially lagged, independent variables WX; and ε is the error term. The term W denotes the spatial weight matrix and reflects the geographic relationship that can be specified using various methods like distance- and contiguity-based ones. LeSage and Pace (2014) suggested that spatial regression results are insensitive to the choice of the spatial weight

[6] To differentiate in Equation (11), γ is used here.

matrix if the spatial model is correctly specified. In this analysis, queen contiguity is used, where two regions i and j are neighbors if they share at least one point or side on their boundaries. The corresponding element in the spatial weight matrix W_{ij} is 1, and W_{ij} equals 0 otherwise.

Bayesian spatial econometric techniques rather than maximum likelihood methods are used. LeSage and Pace (2009, p. 150) indicated that Bayesian spatial econometric techniques outperform maximum likelihood methods as "in small samples parameters may exhibit asymmetry or heavy tailed distributions that deviate from normality." For this reason, Equation(10) is estimated using the Bayesian Markov Chain Monte Carlo (MCMC) method. Generally, let y denote the whole data and θ represent a vector of parameters of interest. The posterior distribution of the parameters, $\pi(\theta \mid y)$, is expressed as:

$$\pi(\theta \mid y) = \frac{\pi(y \mid \theta)\pi(\theta)}{\pi(y)} \tag{11}$$

where $\pi(\theta)$ is the prior probability density function for θ; $\pi(y \mid \theta)$ is the density function for y when the parameter value is θ; and $\pi(y)$ is a constant term and normalizes the posterior distribution. Because $\pi(y)$ is free from the parameter vector θ, Equation (11) is summarized as the Bayesian phrase, the posterior is proportional to the likelihood times the prior and can also be rewritten as:

$$\pi(\theta \mid y) \propto \pi(y \mid \theta)\pi(\theta) \tag{12}$$

Markov chain Monte Carlo (MCMC) methods are used to draw inferences regarding the parameters. Specifically, the Gibbs sampling procedure is used to generate samples of θ and ρ, whereas the Metropolis-Hasting algorithm is used to generate ρ [7]. The prior distribution of the β parameter is a multivariate normal distribution with a mean of zero and a covariance of 10,000$\times I_k$: The prior values for σ come from an inverse gamma distribution with both shape and scale parameter as 0. The prior values for the ρ parameter come from a univariate normal distribution with a mean of 0 and a standard deviation of 10,000. Each model was run for 56,000 iterations with the initial 6,000 discarded as burn-in iterations. The removal of these iterations is useful because the initialized values of the parameters might be unstable.

[7] For more information about these algorithms, see Lacombe (2008) and LeSage and Pace (2009).

4 Empirical Results

4.1 Instability models

Table 2: Effect estimates of instability models

Model 1	Direct effects	Estimates t-statistic	Indirect effects	Estimates t-statistic	Total effects	Estimates t-statistic
HHIS	9.605***	3.088	5.191	0.962	14.796**	1.987
POP	0.101***	2.765	0.097	1.649	0.198***	2.629
EDU	-0.021**	-2.071	-0.017	-1.009	-0.038*	-1.696
NONWHITE	-0.006	-1.098	0.012	1.521	0.005	0.615
INCOME	0.009**	2.063	-0.006	-0.850	0.003	0.372
GOODS	0.014*	1.878	-0.037***	-3.076	-0.023	-1.570
ρ					0.402***	9.643
Model 2	Direct effects	Estimates t-statistic	Indirect effects	Estimates t-statistic	Total effects	Estimates t-statistic
HHIC	5.197***	5.749	4.500***	2.995	9.697***	4.949
POP	0.085**	2.424	0.070	1.322	0.155**	2.352
EDU	-0.021**	-2.187	-0.014	-0.966	-0.036*	-1.783
NONWHITE	-0.006	-1.001	0.010	1.297	0.004	0.475
INCOME	0.009**	2.031	-0.006	-0.935	0.003	0.383
GOODS	0.012	1.615	-0.037***	-3.365	-0.025*	-1.889
ρ					0.351***	8.085
Model 3	Direct effects	Estimates t-statistic	Indirect effects	Estimates t-statistic	Total effects	Estimates t-statistic
MHHI	2.128***	5.175	1.438**	2.183	3.566***	3.926
POP	-0.063	-1.224	-0.018	-0.236	-0.081	-0.759
EDU	-0.024**	-2.442	-0.021	-1.317	-0.045**	-2.130
NONWHITE	-0.003	-0.604	0.010	1.334	0.007	0.794
INCOME	0.011**	2.459	-0.004	-0.572	0.007	0.850
GOODS	0.006	0.832	-0.039***	-3.271	-0.033**	-2.283
ρ					0.373***	8.920

Notes: Note: Significance levels: * for 10%, ** for 5%; *** for 1%.

Table 2 presents the estimation results of three instability models that use three different diversity measures (HHIS, HHIC and MHHI). As the coefficient of the spatially lagged dependent variable, ρ, is statistically significant in each model, the economic stability of an MSA can be impacted by the instability of neighboring MSAs. Unlike the OLS regressions, the estimated βs in Equation (10) cannot be directly interpreted as marginal effects because of potential spatial dependence in the variables (LeSage and Dominguez, 2012). Instead, following LeSage and Pace (2009), the direct, indirect, and total effects were estimated. Note that the direct and indirect effects here can possibly move in opposite directions.

Focusing on the control variables, the population size in Models 1 and 2 is found to contribute to regional economic instability as reflected in the estimated direct and total effects. An MSA with a larger population appears to increase the economic instability of the MSA and its neighbors. By comparison, the population size is statistically insignificant in Model 3. Meanwhile, the estimated direct and total effects of the education attainment variable are negative and significant in Models 1-3, indicating that a better educated population in an MSA seems to reduce its economic instability. Conversely, the indirect effect estimate is insignificant. Furthermore, the nonwhite variable seems to be insignificant and the direct of the income variable is significant in Models 1-3. Finally, the effect of employment in goods-producing sectors on economic stability is mixed when different diversity measures are used.

Turning to the diversity variable, the estimated direct and total effects of economic diversity are positive and statistically significant in Model 1. This result is in line with the portfolio theory that a regions economic diversity contributes to its stability in economic activities. Conversely, the positive indirect effect is not significant as reflected in the t statistics. This, however, is in conflict with previous studies on the spatial spillover effects of economic diversity as suggested by, Trendle (2006), Deller and Watson (2016) and Watson and Deller (2017). In Model 2, the estimated direct, indirect and total effects of economic diversity are significant. Similarly, the positive and significant direct, indirect and total effects in Model 3 suggest that the economic instability of an MSA can be influenced by its own industry mix as well as its neighbors economic structures. Overall, after controlling for industrial, demographical and economic variables, economic diversity is still positively associated with economic stability, although different measures of diversity can alter the impact and statistical significance of economic diversity.

Table 3: Effect estimates of growth models

Model 4	Direct effects	Estimates t-statistic	Indirect effects	Estimates t-statistic	Total effects	Estimates t-statistic
HHIS	7.117	0.811	-21.411	-1.504	-14.294	-0.742
POP	0.616***	5.646	-0.099	-0.623	0.516***	2.596
EDU	0.106***	3.527	-0.051	-1.144	0.055	0.932
NONWHITE	-0.072***	-4.039	0.077***	3.470	0.005	0.210
INCOME	-0.069***	-5.202	0.039**	2.068	-0.030	-1.324
GOODS	-0.151***	-6.645	-0.062**	-1.914	-0.213***	-5.625
ρ					0.301***	15.407
Model 5	Direct effects	Estimates t-statistic	Indirect effects	Estimates t-statistic	Total effects	Estimates t-statistic
HHIC	6.361**	2.309	-3.512	-0.807	2.849	0.503
POP	0.581***	5.481	-0.153	-0.980	0.428**	2.263
EDU	0.105***	3.567	-0.053	-1.218	0.052	0.892
NONWHITE	-0.070***	-4.007	0.074***	3.407	0.004	0.180
INCOME	-0.069***	-5.311	0.042**	2.284	-0.027	-1.193
GOODS	-0.157***	-6.954	-0.066**	-2.096	-0.223***	-5.891
ρ					0.306***	14.503
Model 6	Direct effects	Estimates t-statistic	Indirect effects	Estimates t-statistic	Total effects	Estimates t-statistic
MHHI	3.296***	2.689	-2.344	-1.271	0.952	0.376
POP	0.343**	2.240	-0.003	-0.013	0.340	1.133
EDU	0.106***	3.564	-0.051	-1.137	0.055	0.910
NONWHITE	-0.065***	-3.674	0.074***	3.336	0.008	0.345
INCOME	-0.068***	-5.144	0.042**	2.189	-0.026	-1.113
GOODS	-0.169***	-7.397	-0.048	-1.428	-0.218***	-5.593
ρ					0.319***	13.154

Notes: Note: Significance levels: * for 10%, ** for 5%; *** for 1%.

4.2 Growth models

Similar to the case of instability models, the direct, indirect, and total effects of economic diversity on employment growth were estimated in Models 4-6 in Table 3. The spatially lagged dependent variable is statistically significant in each model, indicating that MSAs with high employment growth can encourage the employment growth of their neighbors.

In Models 4-6, the estimated direct effects of all the control variables (population size, education attainment, nonwhite, income and goods) are significant, although there are variations in the statistical significance of the indirect and total effects. Population size is positively and significantly associated with employment growth in terms of direct and total effects, indicating that population size contributes to employment growth in MSAs during the study period from 2000 to 2002. As the population variable was logged, these estimated effects can be directly interpreted as elasticity. For example, in Model 4, an increase of 10 percent in population size would have a direct effect of a six percent employment increase and the total effect of a five percent increase in employment growth. Similarly, the MSAs with a higher education attainment usually have greater employment growth. Moreover, counteracting effects occur in the nonwhite variable and the income variable. The direct effect of these two variables seems to reduce job creation, while their indirect or spatial spillover effects appear to stimulate employment growth. Finally, employment in goods-producing sectors is likely to reduce employment growth as demonstrated by the negative and significant direct and total effects in all models.

Focusing on the diversity variable, in Models 5 and 6, the direct effect seems to contribute to short-term employment growth and is in line with conventional wisdom, the MAR externalities, as well as the theories of Porter (1990, 1998) that specialization can promote economic growth. In comparison, the indirect or spatial spillover effect in Models 4-6 is negative but insignificant. Finally, although the total effect is insignificant in Models 4-6, there appears to be a trade-off between direct and indirect effects as these two effects move in the opposite direction.

5 Discussion

In this analysis, the effects of economic structure on economic stability and growth are studied using three HHI-based economic structure measures. The first two measures quantify the level of employment dispersion among (1) three-digit NAICS sectors (HHIS) and (2) specialized clusters (HHIC). To consider the interplay of these two measures, the MHHI is also used. Based on the empirical results, there are several interesting points for discussion.

First, both industry and cluster diversity seem to contribute to economic stability. In Models 1-2, the estimated direct and total effects of the diversity variable (HHIS or HHIC) is positive and significant. When the diversity of both sectors and clusters are considered in Model 3, the estimated direct, indirect and total effects of economic diversity on economic stability are positive and significant. In this regard, this analysis confirms that not only industrial diversity but also the diversity of specialized clusters are positively associated with economic stability. In short, for a given region, both industry and cluster portfolios can contribute to economic stability.

Second, unlike the instability models, the effect of industrial diversity on economic growth differs from that effect of cluster diversity. In Model 4, the effect of industrial diversity is statistically insignificant and in line with Hong and Xiao (2016), suggesting that the overall industry diversity hardly impacts employment growth. By comparison, as demonstrated in the estimated direct effect in Model 5, the diversity of clusters is positively and significantly associated with employment growth. Perhaps, this result can be explained be the MAR externalities and theories of Porter (1990, 1998) rather than Jacobs (1969) externalities. Similarly, the direct effect of the diversity variable in Model 6 is positive and significant.

Third, as reflected in both instability and growth models, measuring the economic diversity of specialized clusters and industrial diversity simultaneously contributes to revealing more effects more revealed effects of diversity on economic stability and growth than measuring industrial diversity alone. Many authors (e.g. Conroy, 1975; Kort, 1981; Siegel et al., 1995; Wagner and Deller, 1998) have considered inappropriate measures of economic diversity as one of the factors[8] that contribute to the inconsistency between theoretical assumption and empirical evidence of the relationship between economic structure and regional economic performance. Interpreting economic diversity as both industry and cluster diversity could improve existing economic diversity measures. Although only HHI is used in this analysis, these improvements can also be applied to other diversity measures such as the national average and the entropy index.

Finally, of special relevance here is research on related and unrelated variety[9] in economic geography such as Frenken et al. (2007) and Boschma et al. (2012), where the entropy index is used to measure different types of

[8] Other factors include highly aggregated data sets, overly simplistic statistical modeling methods and others.

[9] For a comprehensive review of recent research on related variety, see Content and Frenken (2016).

variety. Specifically, based on the Standard Industrial Classification (SIC) scheme , Frenken et al. (2007) measured unrelated variety as the average employment entropy across two-digit industries and total variety as the average employment entropy between five-digit industries. The corresponding related variety equals the difference between the total entropy and the unrelated entropy. Similarly, Boschma et al. (2012) indicated that related and unrelated variety can also be defined based on Porter's (2003) definition of clusters; namely, unrelated variety can be measured among clusters and total variety can be calculated among sectors. As such, the unrelated variety measure of Boschma et al. (2012) displays technical similarities with the cluster diversity measure (HHIC). However, these studies neither explicitly emphasize that economic clusters should be specialized relative to the nation (LQ $\geq$ 1), nor aimed at interpreting economic diversity as the presence of multiple specializations, which is the course pursued in this paper.

6 Conclusions

This paper develops a measure to interpret the diversity of economic specializations and emphasizes the coexistence of economic diversity and specialization. It also studies the effects of industry and cluster diversity on regional economic performance. The empirical evidence confirms that both industry and cluster diversity can contribute to economic stability, yet also suggests that only cluster diversity promotes employment growth. Together with Hong and Xiao (2016), this analysis empirically confirms that one region can simultaneously pursue economic growth and stability by promoting diversified specializations.

Table 4: A typology of specialization and diversification in terms of sectors and clusters

	Specialize sector(s)	Diversify sector(s)
Specialize cluster(s)	Type 1: Reinforcement	Type 2: Supplement
Diversify cluster(s)	Type 3: Replication	Type 4: Transplantation

The findings of this analysis also remind economic development researchers and practitioners to consider the underlying relationship between targeted sectors and their linked clusters in industrial recruitment activities. Based on Martin and Sunley (2006) and Boschma et al. (2017), Table 4 enumerates four possible types of economic structure-based development policies that consider this relationship. Reinforcement (Type 1) represents pure specialization at both sector and cluster levels. After adopting economic development policies of this type, regions would experience faster economic growth in the short term. Yet, it is not recommended to specialize only in these clusters in the long run, because a limited number of specializations might be severely impacted by external economic downturns, or "do not place a regions employment eggs in one industry or cluster basket." By comparison, Supplement (Type 2) illustrates a case that the targeted sectors improve the diversity of sectors while reducing the diversity of clusters. Development polices of this type are common nowadays. For example, Jackson's (2015) clusters and diversification strategy (CADS) can be used to identify sectors that fail to support existing economic clusters in terms of supply deficits. Economic development policies focusing on these sectors can promote sector-level economic diversity while decreasing cluster-level diversity; in other words, existing economic clusters would be supplemented in terms of supply. Replication (Type 3) demonstrates a situation where the targeted sectors enhance the economic diversity of clusters while reducing the diversity of sectors. Frenken et al. (2007) indicated to import sectors that are closely related to existing economic structure to be potential clusters. Transplantation (Type 4) indicates complete diversification in the lens of both sectors and clusters. This diversification process can be referred to as importing popular or advanced sectors without fully considering existing regional economic structures when comparing it to Type 3 development policies. Although theoretically feasible in industry targeting and recruiting procedures, it is not suggested as, "one should take existing regional competences as building blocks to broaden the economic base of the region" (Frenken et al., 2007, p. 696).

There are several potential directions for future research. The relationship between cluster and industry diversity should be studied. For example, which one has the priority in regional economic development? Although Desrochers and Sautet (2008) and Hong and Xiao (2016) suggested that overly specialized economies should enhance industry diversity first and then promote specializations as a diversified economy is the prerequisite for the emergence of diverse specializations, this preference has not been examined empirically. Apart from the HHIC—a cross-fertilization of Delgado et al.'s (2016) cluster template, location quotient, and the Herfindahl Hirschman Index—developed in this paper, it is also interesting to develop other measures to meaningfully quantify cluster diversity (e.g. Slaper et al., 2018). In addition, based on the identified typology of structure-based development strategies in Table 4, future research could further develop this typology in such analytical dimensions as key actors, industry targeting methods and risks. With a deeper understanding of economic structures, both specialization and diversity can better benefit regional economic development.

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