EFFECTS OF ECONOMIC STRUCTURE ON REGIONAL ECONOMIC PERFORMANCE

A Dissertation

by

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ABSTRACT

Since the most recent recession, many local governments, which excessively paid attention to economic growth, have undergone tremendous difficulties caused by severe fluctuations. It shows that economic stability also has to be considered as another critical factor that constitutes regional economic performance. Thus, in this dissertation, I evaluate regional economic performance in terms of both growth and stability.

In most previous studies, economic structure was found to be a factor that can affect both growth and stability at the same time. However, in terms of measuring economic structure, diversity and specialization have been commonly treated as the exact opposite, increasing in one means decreasing in the other. Some researchers recognized the existence of multiple specializations in an economy but this concept has never been operationalized and empirically tested. Therefore, I extend the body of previous research by formulating an indicator to empirically measure multiple specializations in regional economies and examine the effect of multiple specializations on both growth and stability in one framework.

Moreover, the economic structural effects can be estimated differently depending on the macro-economic situations. However, previous studies rarely considered the effects of macro-economic situations when investigating the effect of economic structure. Thus, to overcome this limitation, I apply panel analysis for the same statistical models in the above using the panel data which were constructed with four different time periods based on different macro-economic situations.

The empirical analysis in this study finds that multiple specializations might positively affect economic growth while diversity can hinder growth. Otherwise, this study finds that increasing the levels of both diversity and multiple specializations can help regions to promote economic stability. It suggests that a region with a multiply specialized economic structure is more likely to experience both growth and stability at the same time.

Additionally, the results of panel analyses inform that the effects of economic structure on growth vary across different macroeconomic situations while these structural effects on stability are consistently estimated, regardless of macroeconomic situations. This suggests that the economic development strategy using economic structure may indicate the different effectiveness by their objectives (i.e., growth or stability) or the macro-economic situations (i.e., boom or bust).

DEDICATION

To my Lord Jesus Christ,

and

my late father, Sung Yu Hong

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CHAPTER I

INTRODUCTION

1.1 Problem Statement

To achieve the goal of economic growth, local governments annually spend a great deal of their budget on providing a variety of economic development incentives. Specifically, Thomas (2000) estimated the size of total state and local government expenditures on economic development incentives in the U.S. was about $49 billion in 1996. As practical policy tools, local governments implement strategies such as using tax abatement to lure new industries (Peter & Fisher, 2002), launching assisted venture capital programs to incubate new businesses (Barkley, Markley, & Rubin, 2001), or building industrial parks to develop industrial clusters (Porter, 2000). While there is empirical evidence to suggest that these incentives are positively correlated with local governments' primary goal of economic growth (Peters & Fisher, 2002; Wasylenko, 1997), it is true that there is still skepticism about the practical effectiveness of these incentives. More specifically, new jobs created through these incentives may go to people who immigrated from other regions rather than to unemployed natives living in that region (Bartik, 1991). Additionally, there is a possibility that firms or industries that benefit from these incentives will later relocate to other regions (Eisinger, 1988; Marston, 1985).

Moreover, while these criticisms were mostly concerned with economic development incentives not being as effective as one would wish in promoting regional economic growth, there is a fundamental drawback in focusing only on growth because *economic growth is not the only objective for regional development*. Local governments with excessive attention on economic growth may tend to forget other important aspects of economic performance such as economic stability.

There are a few reasons why economic stability is an indispensable factor in evaluating regional economic performance. First, economic instability often produces negative consequences. In a highly unstable or risky economy, participants live well in the boom periods. During the economic boom, wages and household consumption increase and unemployment rates decrease. However, the reverse is observed during an economic bust. Wages are stagnant or going down, layoffs occur and economically stressed households cut their consumption (Spelman, 2006). Specifically, by calculating the amount of change in per captia consumption provoked by fluctuations, Barlevy (2004) estimated the direct cost of economic instability can potentially reach more than $200 billion per year in the United States. In addition, economic instability also has social costs related to the quality of life. Specifically, employment insecurity caused by severe fluctuations was found to correlate with severe anxiety, a decrease of self-esteem, depression, and alcohol abuse (Dooley & Prause, 2004; Feldman, 1996; McKee-Ryan, Song, Wanberg, & Kinicki, 2005). Moreover, in terms of local government financing, because most cities and counties obtain their revenues from property and retail taxes, the level and quality of public infrastructure, which is mostly provided by local government, can be affected by economic instability (Spelman, 2006).

In the body of literature that investigates regional economic performance measured by economic growth and stability (such as Blumenthal, Wolman, & Hill, 2009;

Donegan, Drucker, Goldstein, Lowe, & Malizia, 2008), researchers found that economic structure can affect both economic growth and stability at the same time. Economic structure is the composition of economic sectors or industries in a regional economy. It has usually been measured by the distribution of employment among the sectors or industries in a region. Specifically, when the employment in a region is more evenly distributed among various sectors, that economic structure is said to have a high level of diversity. However, if the employment in a region is concentrated in only a limited number of sectors, the extent of specialization in that economic structure is considered to be high. Most empirical studies have consistently found diversity to be a significant factor for enhancing economic stability (Dissart, 2003). They suggest that a region with a more diverse industrial base would be more stable than regions with only one or two specialized economic sectors (Chinitz, 1961; Gilchrist & St. Louis, 1991; McLaughlin, 1930; Sherwood-Call, 1990). In contrast, the effect of economic diversity on regional economic growth is less conclusive. In fact, there has been a debate on which economic structure – economic diversity or specialization – is more effective in helping regional economic growth (Feldman & Audretsch, 1999; Harrison, Kelley, & Gant, 1996). For instance, Glaeser, Kallal, Scheinkman, and Shleifer (1992) found that diversity has positive effects on employment growth while Henderson, Kuncoro, and Turner (1995) discovered that specialization is positively correlated with employment growth. Among these previous studies, the notable fact is that, although growth and stability are both important aspects of regional economic performance, there have been few empirical studies that examine the effect of economic structure on both economic growth and stability in one coherent framework.

Moreover, previous studies on economic structure are criticized for the dichotomous treatment of economic structure as either diversified or specialized. They usually regard economic diversity as the opposite of economic specialization. But diversity does not necessarily indicate the absence of specialization. For example, metropolitan areas can be specialized in multiple industrial pursuits, called *multiple specializations*. Malizia and Ke (1993) conceptualized that specializations in multiple sectors can both capture the benefits of specialization for growth and, at the same time, foster regional economic stability by compensating for one another when one sector is negatively affected by severe fluctuations. To date, the concept of multiple specializations has been only theoretically mentioned, but not empirically tested. As such, Dissart (2003) argued that there is a need to empirically capture and examine the effect of multiple specializations. Therefore, in this dissertation, I examine the extent to which economic structure has affected regional economic performance – growth and stability – in the United States by applying various measures of economic structure including multiple specializations.

1.2 Contributions

This study contributes to the previous literature in three important ways. First, while previous studies on regional economic performance have focused more on growth, this study provides a more balanced and comprehensive view by also considering (in)stability. Second, in terms of measuring economic structure, this study suggests a new indicator that measures multiple specializations in the economy. I empirically tested the effects of multiple specializations on economic performance using this indicator. Third, this study explored whether different macro-economic situations affect the relationship between economic structures and regional economic performance.

Two cross-sectional models – one for growth and another for instability – were estimated using the *County Business Pattern* data from 353 MSAs throughout the period from 1998 to 2010. Additionally, two panel models were also estimated over short time periods to examine whether the effects of economic structure changed during different macroeconomic situations such as booms and busts. In the results of the growth models, I found that multiple specializations raised the employment growth rate in MSAs while diversity lowered the growth rate. However, these effects attenuated during economic boom periods. Additionally, in the results of models predicting instability, it was found that both diversity and multiple specializations helped regions to enhance their employment stability. Furthermore, unlike the case of growth, the effects of economic structure on instability did not display much variation during economic boom periods.

This study also has policy implications for local governments. When local governments spend their money on economic development, they may as well use their budget to establish appropriate economic structures to help local governments achieve both economic growth and stability. More specifically, the results of this study suggested that, in order to achieve both growth and stability, rather than wasting money on blindly attracting or recruiting new sectors, local governments need to focus on developing multiple specializations based on existing potential sectors.

1.3 Organization of the Study

The remainder of this study is organized as follows: Chapter 2 reviews the literature on economic structure and economic performance, and presents the research questions and working hypotheses. Chapter 3 discusses a variety of economic structure measurements and introduces a novel indicator for measuring multiple specializations. Chapter 4 presents the research design and discusses the analytical methods that will be employed, including model specification and the modeling strategy to be employed. Chapter 5 presents and discusses the findings from the empirical analyses. Chapter 6 concludes this study by summarizing the findings, and discussing policy implications and recommendations for future research.

CHAPTER II

ECONOMIC STRUCTURE, GROWTH, AND STABILITY

In this chapter, I review the theories and empirical findings on why and how regional economic growth and stability can be affected by the structure of the economy. This literature review is composed of three sub-sections: Section 2.1 reviews literature on the relationship between economic structure and economic growth; Section 2.2 reviews literature on the relationship between economic structure and economic stability. Section 2.3 identifies the necessity of developing and examining an empirical indicator of multiple specializations, and Section 2.4 evaluates limitations of the existing research.

2.1 Economic Structure and Growth

2.1.1 Two Competing Theories (Diversity versus Specialization)

As depicted in Figure 2.1., economic structure is one of the most important factors related to regional economic growth. There are two competing theories to explain the relationship between economic structure and growth. Both theories acknowledge that the competitive advantage brought by innovations is one of the most important factors to facilitate economic growth in regions and the structure of industries in a region can determine the level of economic growth in that region. Their major difference lies in how economic structure relates to innovation. Jacobs (1969) stated that innovation arises primarily from the knowledge spillover across industrial sectors. She believed that regional economic diversity promotes interactions among various industrial sectors, resulting in knowledge spillovers and ultimately innovation and economic growth. In other words, the transmission of complementary ideas across diverse sectors can help research and development that lead to innovation. For instance, the financial service industry in New York was born from the necessity for cotton merchants to engage in financial transactions (Glaeser et al., 1992). More specifically, Scherer (1982) provided evidence that, considering 263 manufacturing and non-manufacturing industry categories, approximately 70 percent of innovations in a given industry are used outside that industry.

In contrast, Marshall (1890), Arrow (1962), and Romer (1986) argued that innovation is promoted by knowledge spillovers among firms in similar industrial sectors, which is called the MAR theory. The MAR theory claimed that knowledge spillovers are more likely to occur in a specialized economic structure because the knowledge accumulated by a firm in a given industry can be used to the benefit of other firms in that industry. This knowledge transmission is strongly promoted by the concentration of similar economic sectors in a region (Saxenian, 1994). Thus, the specialized economic structure in a region promotes knowledge spillovers within the same or similar sectors and therefore facilitates innovations and economic growth in that region. For example, the microchip production firms in Silicon Valley used to obtain their sources for innovations by interacting with each other in the same microchip production industry (Glaeser et al., 1992). Similarly, Porter (1990) believed that the knowledge spillovers from a specialized economic structure promote economic growth in regions. Porter (1990) contended that developing clusters – geographical concentrations of interconnected companies and institutions in a particular field – is the most effect strategy for local economic development.

Figure 2.1 Economic Structure and Growth

2.1.2 Empirical Findings on Economic Structure and Growth

Previous empirical studies have produced mixed and inconsistent results. These studies can be roughly categorized into two groups by their unit of observation (See Table 2.1). The first group of studies uses the overall economic growth in a region as their dependent variables. The level of diversity is measured in terms of overall economic structure and the effect of specialization is measured by the level of specialization in a few selected individual sectors. The second group of studies took a narrower approach, focusing on the economic growth of a few selected sectors in a region instead of the overall regional economic growth. Because the dependent variable for this group is economic growth in particular sectors in regions, the level of specialization is measured in terms of each selected sector and the diversity is measured by the mix of sectors outside that selected sector.

The empirical studies show little difference in the relationship between growth and economic structure no matter if growth is measured as the growth of the overall economy or growth of a few selected sectors. Diversity in the overall economy was often found to promote growth, whereas specialization in selected sectors was found to have mixed results on growth. Growth has been measured in terms of wages, per capita income, employment, and new firm formations. For wage growth, Glaeser et al. (1992) found that only diversity has a positive effect on wage growth, whereas, in Almeida (2007), only specialization is found to have a positive impact on wage increase. Cingano and Schivardi (2004) found that neither specialization nor diversity has a positive effect on wage growth. The interesting fact in Almeida (2007) is that while the effect of specialization on wage and productivity growth is positive, when growth is measured by employment growth, specialization has a negative effect. This implies using different indicators for measuring economic growth can produce different results.

In addition, three empirical studies have been conducted to examine the effect of overall economic structure on the *growth of per capita income*. All these studies used the same type of unit of analysis (states in the U.S.) although the time spans of analyses are different from each other. Specifically, Attran (1986) tested the effect of diversity on per capita income growth during the 1970s and Wagner and Deller's study (1998) was based on two decades – the 1970s and 1980s. Additionally, the study by Izraeli and Murphy was based on the 1990s. The results of these studies are also mixed. Attran (1986) found that diversity is negatively associated with per capita income growth while Wagner and Deller (1988) observed a positive effect of diversity. Moreover, in Izraeli and Murphy

(2003), the effect of diversity showed a positive sign but it was statistically insignificant. Therefore, these conflicts suggest that different time periods can induce different empirical results. So, there is no general trend in the relationship between diversity and growth.

Moreover, Jacobs' theory is more often supported than the MAR theory by the studies using *employment growth* in both overall economy and a few selected sectors as a proxy for economic growth. Most of these studies on overall economic structure provide evidence that only diversity of overall economic structure favors employment growth, whereas a limited number of studies indicate that specialization alone has a positive effect. Furthermore, it is also observed that high specialization in a few selected sectors is even negatively related to employment growth rates (Cingano & Schivardi, 2004; Combes, 2000a; Glaeser et al., 1992). Cingano and Schivardi (2004) and Combes (2000a) explained the negative effect of specialization on employment growth by congestion externalities or the high costs of reemployment reallocation arising from specialization.

Table 2.1 Empirical Evidence on the Relationship between Economic Structure and Growth

	Study	Measure			Observation Unit	Effects on Growth	
		Specialization	Diversity	Growth		Specialization	Diversity
Dependent variable: Growth in sectors	Glaeser et al. (1992)	LQ	Ratio of city's other top five industries' employment	Employment / Wages	6 largest industries in standard metropolitan areas (SMAs)	Negative for employment; Insignificant for wages	Positive for employment; Negative for wages
	Henderson et al. (1995)	Ratio of own industry employment	Inverse of Hirschman	Employment	5 industrial sectors in SMSs	Positive	Positive
	Baptista & Swann (1999)	-	Hirschman	New firm formation	Computer industries in the US and UK	Insignificant	-
	Combes (2000a)	LQ	Inverse of Hirschman	Employment	Service and industry sectors in local areas in France	Negative effects from both service and industry sectors	Positive effect from service sector; Negative effect from industry sector
	Rosenthal & Strange (2003)	Size of own industry employment	Hirschman	New firm formation	SIC 2-digit industries in zip code boundary	Positive	Positive
	Cingano & Schivardi (2004)	Share of sectoral city employment[1]	Hirschman	Productivity/ Employment/ Wages	Manufacturing sector in Italian local labor Systems (LLS)[2]	Positive for productivity; Negative for employment; Insignificant for wages	Insignificant for productivity; Positive for employment; Insignificant for wages

[1] For example, the share of sectoral city employment for the manufacturing sector is calculated by dividing manufacturing employment in a city with total manufacturing employment in all cities.

[2] The Italian local labor systems (LLS) are defined as groups of municipalities characterized by a self-contained labor market, as determined by the National Statistical Institute (NSI) on the basis of the degree of workday commuting by the resident population (Cingano and Schivardi, 2004, p.726).

Table 2.1 Continued

	Study	Measure			Observation Unit	Effects on Growth	
		Specialization	Diversity	Growth		Specialization	Diversity
Dependent variable: Growth in sectors	Almeida (2007)	LQ	Inverse of Hirschman	Wages/ Employment/ Productivity	Manufacturing sectors in Portuguese regions	Positive for productivity/ wages Negative for employment	Insignificant for all three dependent variables
	van Oort & Stam (2006)	LQ for three sectors -ICT[3], Manufacturing, Business service	Locational Gini-coefficient	New firm formation	ICT industries in 580 Dutch municipalities	Positive from ICT and Business service sectors	Positive
	Drucker (2011)	Ratio of 5 largest dominant firms	Hirschman	Employment	Manufacturing sectors in MSAs	Negative	Insignificant
	Shuai (2013)	LQ	Hachman[4]	Employment	Locality-major sectors in Virginia	Positive	Positive
Dependent variable: Overall growth in geographical unit	Attran (1986)	-	Entropy	Per capita income	States	-	Negative
	Wagner and Deller (1998)	-	Diversity index based on Input-Output model	Per capita income	States	-	Positive
	Izraeli and Murphy (2003)	-	Hirschman	Per capita income	States	-	Insignificant
	Frenken et al. (2007)	LOS-index[5]	Entropy	Employment	Spatial labor market regions	Negative	Insignificant

[3] ICT stands for Information & Communication Tech (ICT) industrial sector
[4] The Hachman index is computed as the inverse of the sum of the weighted location quotients of all industries in a locality (Durrant & Shumway, 2004).
[5] The Los-index (Los, 2000) captures the level of technological relatedness among industrial sectors in regions by calculating the level of similarity between the input mixes of two sectors in the Input-Out tables. If all the pairs of industrial sectors in a region are based on the same input mixes, the Los-index will be equal to 1. In this case, that region is considered to be fully specialized by one industrial sector.

Three studies specifically investigated the effect of economic structure on *new firm formation*. Rosenthal and Strange (2003) measured the levels of diversity and specialization using the employment data at the zip code level and estimated the effects of them on new firm formation in six SIC[6] 2-digit level industrial sectors. van Oort and Stam (2006) examined the effects of overall diversity and specializations in three selected sectors - the Information and Communication Tech (ICT), manufacturing, and business service sectors on the new firm formation in the ICT in 508 Dutch municipalities. Both found specialization in the sectors of study and diversity in the overall economy to be positively corrected with the number of new firms. Therefore, both Jacobs and MAR theories are supported. However, Baptista and Swann (1999), who focused on the computer industries in the US and UK, found an insignificant effect of specialization in the computer industrial sector on the entry of new firms.

Furthermore, the studies that investigated the effect of diversity and specialization by the different stages of *product cycle* in industrial sectors found the evidence that both diversity and specialization might positively affect employment growth simultaneously during some specific stages of the product cycle (Henderson et al., 1995). More specifically, Henderson et al. (1995) found, for new high-tech industries, they found positive effects of both specialization and diversity in manufacturing sectors on employment growth.

[6] SIC stands for Standard Industrial Classification system, which is used for classifying industries by a four-digit numbering code.

According to Beaudry and Schiffauerova (2009)[7], the conflict or difference in the results could also be explained by other methodological issues such as geographical units of analysis, industrial classification level, types of measures for economic structure, the types of sectors or industries used in the analysis, and the research time span. For the level of industrial classification and geographical units, specifically, the results from Beaudry and Schiffauerova (2009) indicated that the detailed industrial level with high geographical aggregation, i.e. states or metropolitan areas, was much more likely to help us detect the effects of both specialization and diversity than the broad industrial level with low geographical disaggregation, i.e. counties or census tracks. In addition, for the types of sectors used in the analysis, in a low-tech sector, specialization was found to have a stronger effect than diversity, whereas, in a high-tech sector, diversity tended to more positively affect economic growth (Beaudry and Schiffauerova, 2009). Therefore, in order to precisely estimate the effect of economic structure on economic growth, various other factors should be controlled and considered in the research.

[7] A meta-analysis on the relationship between economic structure and growth by employing a review of 67 empirical articles

2.2 Economic Structure and Stability

2.2.1 Theory: Economic Diversity Supports Economic Stability

> *"As a rule, since no two businesses have exactly the same seasonal and cyclical swings, the more types of production and trade are represented, the more stable will be that community's business" (McLaughlin, 1930, p.133)*

Why should economic structure affect regional economic stability? The answer is simple. In stock market investments, a good investor will not put all his eggs in one basket. This is because when there is an external shock to that basket, it is possible to lose all the eggs at once. The best way to avoid this high risk is to put the eggs in many different baskets. In other words, the investment portfolio should be diversified to reduce the risk. This traditional wisdom is also true for local economies. Specifically, even if specialization may be a key to rapid economic growth, many scholars repeatedly warn that specialization in a small number of economic sectors or industries can intensify the level of economic instability (Baldwin & Brown, 2004; Conroy, 1975; Ezcurra, 2011; Kort, 1981; Malizia & Ke, 1993; Trendle, 2006). This is because the economy of a region with a specialized economic structure may be vulnerable to downturns in those specialized economic sectors. The market basis for specialized sectors in a region can be undermined if other regions find cheaper suppliers or improve production processes (Attaran & Zwick, 1987). Similarly, various external perturbations such as natural disasters can affect those specialized sectors. For example, the economic structure of

Richmond, Virginia is highly specialized in the tobacco industry. If a natural disaster negatively affects the tobacco industry, the local economy of Richmond would be severely damaged (Spellman, 2006).

Businesses in a region are differently affected by various external shocks or supply-demand fluctuations. As Figure 2.2 shows, suppose Curve A is the current business cycle of the businesses based on rice production in one region. Assuming wheat perfectly supplements rice, by attracting an industry based on wheat production that has a cycle such as that of Curve B, this region may reduce its economic instability from the fluctuations of Curve A to the fluctuations of Curve C indicating economic stability. Hence, diversifying economic structure can be an appropriate strategy for stabilizing the economic cycle in a way similar to the target cycle, Curve C.

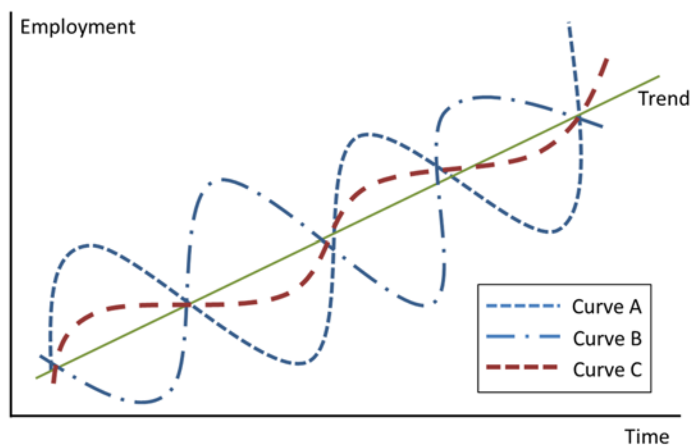

Figure 2.2 Cyclical Patterns of Industries in Regions. Adapted from "Regional Cyclical Instability: An Empirical Examination of Wage, Hours and Employment Adjustments, and an Application of the Portfolio Variance Technique," by J. A. Kurre and B. R. Weller, 1989, *Regional Studies*, 23(4), p. 323. Copyright 2013 by Talyor & Francis. Adapted with permission

Therefore, the greater the number of sectors or industries in a region, and the more evenly distributed the employment among these various economic entities in a region, the less likely it is that the region will be affected by serious economic recession (Kort, 1981).

From the perspective of regional economic development policy, economic instability is generally recognized as an undesirable state (Siegel, Alwang, & Johnson, 1995; Wagner, 2000). This is because a high level of economic instability is directly associated with job insecurity such as unemployment or underemployment. This job insecurity might cause various social problems in the population, such as severe anxiety, a decrease in self-esteem, depression, and alcohol abuse (Dooley & Prause, 2004; Feldman, 1996; McKee-Ryan, Song, Wanberg, & Kinicki, 2005). For this reason, policymakers have regarded the reduction of economic instability as an important issue for regional economic development (Schoening & Sweeney, 1992). Hence, if economic diversity is positively associated with reducing instability, diversifying industries or sectors might be an appropriate policy for regions wishing to stabilize their economies (Gilchrist & St. Louis, 1991; Sherwood-Call, 1990).

2.2.2 Empirical Evidence of the Effect of Diversity on Stability

While the theories about the relationship between economic structure and growth are inconclusive, the theory concerning the relationship between economic structure and stability is rather consistent and definitive: *Economic diversity helps regions secure their economic stability.*

Table 2.2 Empirical Evidence on the Relationship between Economic Structure and Stability

Study	Measure			Observation Unit	Effects on Stability	
	Speciali -zation	Diversity	Stability		Specialization	Diversity
Siegel (1966)	-	Employment % of durable goods producing industries	Amplitude of employment cycle in industries or regions	SMSAs	-	Positive
Cutler & Hansz (1971)	-			SMSAs	-	Positive
Cho & McDougall (1978)	-			SMSAs	-	Positive
Lynch (1979)	-	National Average Index	Variation in total employment growth rates	States	-	Positive
Brewer & Moomaw (1985)	-	National Average Index; Ogive index	Regional Economic Instability (REI) indicator[8] of employment	SMSAs	-	Positive
Jackson (1984)	-	National Average Index; Ogive index	Standard deviation of the fluctuations	Counties in Illinois	-	Insignificant
Attaran (1986)	-	Theil's Entropy	Standard deviation of unemployment and per capita income	States	-	Positive
Attaran & Zwick (1987)	-			Counties in Oregon	-	Positive
Smith & Gibson (1988)	-		REI of employment	Nonmetropolitan counties in Idaho	-	Positive
Malizia & Ke (1993)	-			MSAs	-	Positive
Conroy (1975)	-	Portfolio variance	Coefficient of variation of residuals from a quadratic trend of manufacturing employment	SMSAs	-	Positive
Wagner & Deller (1998)	-	Input-Output approach	Variance in the average annual unemployment rate	States	-	Positive

[8] The Regional Economic Instability (REI) indicator is first introduced by Kort (1981), and is calculated as the average of deviation from the employment trend and divided by trend employment.

As a matter of fact, most empirical results strongly support the theory that diversity promotes economic stability (See Table 2.2). In terms of measuring economic instability, while there are several means of measuring economic diversity, economic instability has been measured based on a consistent concept (Dissart, 2003). Except for some early studies which used the amplitude of the employment cycle in industries or regions to measure instability, i.e., Sigel (1966), Cutler and Hansz (1971) and Cho and McDougall (1978), most studies used variance-based statistics. They usually applied the variance or standard deviation of economic outcomes such as employment growth, unemployment rates, or per capita income to gauge economic instability (Attran, 1986; Attran & Zwick, 1987; Jackson, 1984; Lynch, 1979; Wagner & Deller, 1998). Furthermore, by extending these variance measures of instability while considering economic trends, Kort (1981) developed the regional economic instability index (REI), which measures an average deviation between actual employment and predicted employment from a time trend regression divided by the predicted employment. The superiority of using the REI can be shown by the following simple example. Suppose the growth rate of one area is zero while another area is indicating a constant growth rate. Applying the variance measures of instability, the stagnant area will be revealed as more stable than another area with a consistent growth rate. However, the results of measuring instability using the REI will be equal for both areas. Therefore, by using the REI, we can measure the level of instability controlling for the effect of economic trends. The REI was also applied in many previous studies (Brewer & Moomaw, 1985; Malizia & Ke, 1993; and Smith & Gibson, 1988). The important fact is that, as Brewery (1985) remarked, although various measures for instability have been proposed, and they differ somewhat in their treatment of random, seasonal, trend, and cyclical components, these measures of economic instability have in common using a variance-based statistic applied to employment data over time (Brewery, 1985, p. 463).

As presented in Table 2.2, regardless of the types of indicators applied to measure economic instability and diversity, most of the empirical studies about the relationship between economic structure and instability have provided the consistent result that economic diversity is positively associated with reducing economic instability in regions while specialization can cause considerable cyclical fluctuations. Early interest in the relationship between economic structure and stability was provoked by the collapse of manufacturing industries caused by the Great Depression in the 1930s (Domazlicky, 1980). These early studies tried to estimate the effect of the manufacturing sector on economic instability, which was measured by using the amplitude of employment cycle in regions, and supported the premise that economic structure was significantly associated with regional economic cycles (Cho & McDougall, 1978; Cutler & Hansz, 1971; Siegel, 1966).

During the 1970s and 1980s, many studies began to assess a variety of diversity measurements and examine their effects on regional economic instability. As described by Dissart (2003), many kinds of normative diversity measures were introduced and examined: the national average (Lynch, 1979), the Ogive index (Brewer & Moomaw, 1985; Jackson, 1984; Wasylenko & Erickson, 1978), and the entropy index (Attaran, 1986; Attaran & Zwick, 1987; Malizia & Ke, 1993; Smith & Gibson, 1988). Similar to the early studies, the empirical studies undertaken during this period also provided evidence that a high level of diversity in an economic structure would positively affect reducing economic instability in regions. Furthermore, at that time, developing measurements for economic structure overwhelmed the basic objective of research (estimating the effect of diversity on economic stability) because many scholars tried to simply create a case for their diversity measurements and then attempted to show empirically that their chosen indicators were better than others (Isserman, 1995).

On the other hand, a new phase of research on the relationship between economic structure and instability was initiated by applying financial portfolio theory to regional economics in the mid-1970s (Conroy, 1974, 1975). In this approach, assuming that a region was an investor with an asset portfolio composed of the industrial mix in that region, economic instability was measured in terms of the entailed risk from that asset portfolio in the form of employment variations. In short, the portfolio approach measures the level of diversity by using some types of economic instability. The greatest hallmark of this approach is that the researchers and analysts began to consider both the employment variation in each industry and the interaction with others in the portfolio (Sherwood-Call, 1990). However, although Conroy (1975) tried to estimate the effect of portfolio variance on the instability of manufacturing employment, applying the portfolio approach was not suitable to test the hypotheses concerning the relationship between economic diversity and instability because the portfolio approach measures economic structure using economic instability. In short, the result of measuring economic diversity (independent variable) is not independent of economic instability (dependent variable) (Sherwood-Call, 1990; Siegel, Johnson, & Alwang, 1995). To overcome the limitation of using portfolio analysis, Wagner and Deller (1998) suggested an alternative way to measure the level of diversity by using the Input-Output (I-O) model. They argued that using the I-O model allowed measurement of the level of diversity based on the interrelationships of sectors without concern about the dependency of diversity measures on economic instability. Moreover, they found that the diversity level measured by the I-O model was negatively associated with the variance of the annual unemployment rate. However, using the I-O model is also limited and rarely implemented because of data feasibility issues such as constructing the Input-Output table for various levels of industries and geographical units.

In sum, the results from many previous studies, except for one case of the counties in Illinois, have consistently indicated that the level of economic diversity has a positive association with the economic stability in regions. Moreover, using different types of structure measures, observational units, and research time spans makes no significant difference in the findings on the relationship between economic diversity and instability.

2.3 Effects of Multiple Specializations on Economic Performance

Most previous studies, which investigated the influences of economic structure on regional economic growth or instability, usually applied the same indicator to measure specialization or diversity (as lack of specialization) in the overall economy. In other words, only one indicator was used to measure the overall economic structure, either in the form of a diversity index or a specialization index. This approach treated diversity and specialization as totally opposite concepts: an increase in one meant a decrease in the other. A high level of diversity is often regarded as a low level of specialization in the overall economy. However, regional economy can be specialized in multiple pursuits. As theoretically mentioned by Malizia and Ke (1993), a diversified economic structure does not necessarily indicate the absence of specialized economic sectors.

First, in previous studies about the relationship between economic structure and growth, specialization in economic structure was measured separately from, instead of as part of, the overall economic specialization. Specifically, the empirical studies that simultaneously consider both diversity and specialization tend to capture the effect of diversity from the overall economic structure and to estimate the impacts of specialization from a few selected industries or sectors (Glaeser et al., 1992; Mizuno, Mizutani, & Nakayama, 2006). However, measuring the level of specialization in a few selected sectors is limited because the comparative advantages based on specialized economic sectors can be different across regions and selecting a few sectors may not fully reflect the effects of specialization on regional economic growth. Therefore, there is a need to invent a new collective measure of specialization in the overall economy, which should not just be the opposite of the diversity measures (Dissart, 2003).

Second, the concept of multiple specializations is also expected to have a more active role in the relationship between economic structure and instability. Diversifying economic structure is a type of averaging process: negative impacts from severe fluctuations or shocks would be offset by the industries or sectors that remain relatively healthy during difficult times (Gilchrist & St. Louis, 1991). Similarly, in an economic structure with multiple specializations, this averaging process can also be expected. Furthermore, when some economic sectors are negatively affected by severe fluctuations or shocks, because relatively healthy industries during difficult times are more likely to be specialized under the structure of multiple specializations, the negative impacts can be compensated for more rapidly by extra growth based on such healthy and specialized industries. More specifically, the process of stabilizing an economy can be categorized in two steps: (i) minimizing the negative impact; (ii) recovery from the negative impact. Multiple specializations can help in both steps by averaging the negative effects and helping rapid growth using the specialized sectors, whereas diversity tends to focus only on offsetting the negative impacts. However, the concept of multiple specializations has not been investigated in terms of economic instability.

In sum, although the concept of multiple specializations in economic structure is expected to have a significant effect on regional economic performance, this concept was only theoretically mentioned, not empirically tested. Hence, the effect of multiple specializations needs to be empirically examined by developing a new empirical indicator to measure the level of multiple specializations.

2.4 Evaluation of the Literature

2.4.1 Overall Review

There has been theoretical debate about whether diversity or specialization of the economic structure better promotes regional economic growth. Just as there are heated debates in the theories about the relationship between economic structure and growth, so do empirical studies produce mixed and sometimes contradictory results. Empirical studies have found both diversity and specialization being positively related to growth. Diversity was rarely found to have negative effects on growth whereas specialization in overall economic structure is sometimes negatively associated with growth (Beaudry & Schiffauerova, 2009). On the other hand, the theoretical background for the effect of economic structure on instability is very consistent: Diversity helps regions enhance their economic stability. Most empirical studies also provide evidence that strongly supports this theory.

2.4.2 Limitations of Existing Research

First, previous studies on the relationship between economic structure and regional economic performance have tended to address economic growth and stability separately, although these studies use similar economic structural indicators as their independent variables. It is difficult to find research that investigates the role of economic structure in both growth and stability at the same time. Moreover, it is also true that most of the studies focused more on economic growth than stability. However, considering the negative effects from economic instability, both growth and stability need to be investigated simultaneously to more comprehensively understand regional economic performance. This dissertation expects that economic structure is an important factor that might simultaneously affect both growth and stability. Hence, there is a need to undertake an appropriate investigation of economic structures that can positively affect both economic stability and growth at the same time.

Second, discussion concerning appropriate measures for economic structure is needed to select and examine the effects of economic structure on regional economic performance (Wagner & Deller, 1998). Using improper structural indicators might produce misleading results. For example, using location quotients for measuring specailization in regions may only be appropriate when the population size is sufficiently large. However, if the population size is small, using the absolute size of industries is more suitable for measuring the effect of specialization (Ejermo, 2005). Moreover, a regional economy can be specialized in multiple sectors. This concept of multiple specializations, which can have both properties of diversity and specialization, is hardly measured by the existing structure indicators. As previously mentioned in Section 2.3, although multiple specializations might have subtantial effects on both economic growth and stability, the concept of multiple specializations is only theoretically mentioned, but not empirically tested. Therefore, in order to more precisely capture the effects of a variety of economic structure on regional economic performance, this study will try to estimate the effect of multiple specializations on regional economic performance by developing a new empirical indicator.

Third, previous studies rarely took into account of the effects of macro-economic situations on regional economic performance. The effects of economic structure on regional economic performance can be estimated differently depending on the time span of the study (Beaudry & Schiffauerova, 2009). Specifically, according to macro-economic situations, different roles of economic structure might be expected. Thus, the estimation results for economic diversity (specialization) during an economic boom might be different from those based on a period of economic bust. For example, if an economic boom is based predominantly on rapid growth in one specific economic sector (e.g., the boom in information technology at the end of the 1990s), the effect of diversity on growth may not be particularly significant during this time period. Otherwise, the positive effect of diversity on reducing economic instability might be consistent regardless of macro-economic situations. However, most previous studies were conducted using a cross-sectional approach based on only one time period rather than considering the effect of different macro-economic situations (Beaudry & Schiffauerova, 2009). Therefore, it is necessary to examine how the relationship between economic structure and performance in regions might be different depending on the different macro-economic situations

Fourth, most previous empirical works are limited in that they used inappropriate model specifications (Malizia & Ke, 1993; Trendle, 2006). In previous literature, the most significant problem was to estimate the effect of economic structure without proper control variables (Malizia & Ke, 1993). Economic performance in regions can be explained by a variety of factors other than the types of economic structure. Thus, it is very important to consider the proper control factors, particularly for the effects from individual sectors on regional economic performance, when specifying the statistical model. For instance, Smith and Gibson (1988) showed that having more stable sectors is more important for securing regional economic stability than industrial diversification. Furthermore, the estimation method employed must be appropriate for the data sets being used (Trendle, 2006). Because studies investigating economic performance in regions usually employ spatial data sets, specific methods (e.g., spatial econometrics) have to be used to take account of spatial dependence in the residual that might cause biased and inconsistent estimation results.

CHAPTER III

RESEARCH QUESTIONS AND HYPOTHESES

The extant literature on the relationship between economic structure and regional economic performance leads to the development of four main research questions and associated hypotheses to be tested. In terms of measuring economic structure, because this dissertation essentially focuses on measuring overall economic structure, the same indicator will be used to measure both specialization and diversity at the same time. Thus, a less diversified economic structure is considered a more specialized economic structure. Furthermore, to overcome the limitations of using the same indicator for measuring both diversity and specialization, another structure indicator for multiple specializations will be used as one of the main structural variables. Hence, the testing of hypotheses is primarily composed of estimating the effects of the two main structure indicators – diversity (specialization) and a multiple specializations indicator – on regional economic performance, – growth and stability. The research questions, hypotheses, and the rationales for the hypotheses are delineated below.

RQ1: Which economic structure is the most efficient for achieving high economic growth?

H1.1: The more diversity in a regional economy, the higher the regional economic growth.

Rationale for H1.1: The interaction of complementary ideas across diverse economic sectors can help regions innovate for economic growth (Jacobs, 1969). Although specialization in economic structure is also expected to have a positive association with economic growth (Arrow, 1962; Marshall, 1890; Romer, 1986), in this case, the innovations for economic growth are more likely to come from the knowledge accumulation in a few specialized economic sectors, not the specialization level of the overall economic structure. Therefore, in terms of overall economic structure, it is expected that there is a significant relationship between diversity and growth.

H1.2: The higher proportion of specialized sectors a region has, the higher its level of economic growth.

Rationale for H1.2: As previously suggested, economic growth might be enhanced by a specialized economic structure. Thus, those regions with more specialized economic sectors are also more likely to enjoy better economic growth.

RQ2: Which economic structure can secure regional economic stability?

H2.1: The more diversified an economy, the lower its economic instability

Rationale for H2.1: If the number of sectors or industries is higher in a region, or employment among these entities is more evenly distributed, that region is less likely to be affected by severe fluctuations (Kort, 1981). This is because it is almost impossible that two economic sectors or industries will have exactly the same business cycles. Therefore, the negative impact on one economic sector can be compensated for by the economic performance of other sectors that are relatively healthy when some sectors are negatively affected by fluctuations or external shocks.

H2.2: The higher proportion of specialized sectors a region has, the lower its economic instability

Rationale for H2.2: Multiple specializations have a very similar effect in terms of offsetting negative impacts as a diversified economic structure. In addition, it can be expected that negative impacts will be more rapidly compensated for by extra growth based on healthy sectors when some sectors are negatively affected by fluctuations or external shocks. This is because the relatively healthy sectors during these difficult times are more likely to be specialized under the economic structure of multiple specializations.

RQ3: Which economic structure helps regions accomplish both economic growth and stability simultaneously?

The test results from the above hypotheses (*H1.1 ~ H2.2*) will determine the best economic structure which can enhance both growth and stability. More specifically, the economic structure of multiple specializations is expected to have more of a positive association with both growth and stability at the same time. This is because the concept of multiple specializations can have a combined strength from both diversity and specialization at the same time.

RQ4: Do the relationships between economic structure and performance, which are assumed in the above research questions and hypotheses, hold for different macro-economic situations?

The influence of economic structure on regional economic performance might be different in line with the macro-economic characteristics of the research time span. Specifically, according to economic booms and busts, we can expect different roles of economic structure in both growth and stability. So, to precisely answer research question 4, I divided the overall time span of my research into 4 sub-time periods determined by the macro-economic situations (e.g., boom or recession). After that, I tested the same hypotheses (*H1.1- H2.*2) under these various macro-economic situations.

CHAPTER IV

MEASUREMENTS OF ECONOMIC STRUCTURES

As previously discussed in Chapter 2, the empirical results of estimating the effects of economic structures on regional economic performance – growth and stability – can be different by the way in which the economic structure is measured (Beaudry & Schiffauerova, 2009). In other words, using appropriate indicators for measuring economic structure is an important component in investigating the role of economic structure in regional economic performance. Many previous studies have attempted to empirically measure economic structures by a variety of indicators. From the early method of using a simple share of durable-goods production industries in a region to the recent approach of applying an Input-Output analysis, the measurements of economic structure have developed with the advances of calculation ability and data availability.

This chapter reviews the most frequently used indicators or methods for measuring economic structure. Based on this review, I introduce a new indicator to measure the economic structure of multiple specializations.

4.1 Criteria for Evaluating Economic Structure Indicators

4.1.1 Normative Economic Structure Indicators

The normative indicators usually measure the economic structure based on some type of standard or reference economic structure, e.g., equiproportional or national employment distribution. According to Wagner (2000), the normative indicators such as the entropy index, the Hirchman-Herfindahl index, the national average index, and the Ogive index are the most commonly used measures in empirical studies because they are easy to compute and only require limited demands for data. Thus, in this section, the most frequently used normative indicators are introduced and discussed. Based on the evaluation of each normative indicator using the various criteria, this section will discuss which indicator is more appropriate for the objective of this study.

4.1.2 Evaluation Criteria

There is a need to identify evaluation criteria to discuss the strengths and weaknesses of the normative indicators for measuring economic structure. Analyzing normative structure measures with these evaluation criteria is expected to help us understand the reason why the empirical results of estimating structural effects on regional economic performance can be different by how the economic structure is measured. The following seven criteria are the most frequently used to evaluate the indicators for economic structure or inequality (Palan, 2010).

Absolute indicators versus relative indicators

A variety of normative economic structure indicators can be classified into two groups. The first group measures economic structure in a region with absolute indicators. The absolute indicators attempt to measure economic structure using the distribution of the overall employment among all the industries or sectors in a region. For instance, using an absolute specialization indicator, a region would be disclosed to have a specialized economic structure if a limited number of specific sectors or industries in this region show high shares of the employment. On the other hand, if a large number of industries show similar employment shares in a region, the economic structure of this region would be considered diversified (Aiginger & Davies, 2004).

The second group of indicators measures economic structure based on the deviation of economic structure of a region from national economic structure or the average economic structure of the reference group (i.e., Krugman specialization index or national average index). In other words, the relative indicators measure the economic structure of a region in relation to other regions or nation. More specifically, if the deviation of economic structure between a region and national or reference group is small, that region will be identified as having a high diversity level by these relative indicators. The one virtue of using relative indicators is that, when measuring the level of specialization in an economic structure, they disclose the comparative advantages in a region in relation to other regions. However, using relative indicators might bring biased estimation results about an economic structure. Because the regions with larger employment sizes contribute more to composing a benchmark than the regions with smaller employment sizes when measuring the specialization, the specialization level of the regions with larger employment sizes can be underestimated while the specialization level of the regions with smaller employment sizes can be overestimated. On the contrary, when measuring the diversity level, the larger region can be overestimated while the smaller region can be underestimated (Palan, 2010).

In sum, when a region is specialized in a few specific industries in which other regions are simultaneously specialized, the absolute indicator will show a high level of specialization in that region while the relative indicator will reveal a low level of specialization. However, both types of indicators have been criticized for their arbitrary natures (Brown & Pheasant, 1985; Gratton, 1979). There is no solid rationale or academic background for using these benchmarks or references (Conroy, 1974, 1975). For instance, the Hirschman-Herfindahl index, which is the most representative example of the absolute indicators, uses the uniform employment distribution as its benchmark.

However, using the benchmark of the uniform distribution overlooks the fact that certain types of industries or sectors inherently have a larger employment size, i.e., manufacturing sector, than others. Actually, this large employment size does not necessarily signify specialization but the level of specialization in this sector can be overrepresented by the absolute indicators based on the uniform distribution of employment.

Axiom of anonymity

If the distributions of employment shares of industries or sectors are obtained through permutation, the results of measuring economic structure should be the same for any employment share distributions (Atkinson, 1970; Kolm, 1969). In other words, the calculating order of employment shares of industries or sectors used for constructing the indicators should have no effect on the measured results.

Axiom of progressive transfer

According to this axiom (Atkinson, 1970; Dalton, 1920; Hannah & Kay, 1977; Sen, 1973), in terms of economic structure, if employment is shifted from an industry with a high employment share toward another industry with a low employment share, the level of absolute diversity will increase or the level of absolute specialization will decrease.

Boundaries

Having a defined boundary for measurements is important for clarifying whether the economic structure is highly specialized or diversified. For absolute indicators, when measuring the level of specialization, specialization indicators will show the upper boundary if a region is presented as having all its employment in one industry. On the other hand, in the case of diversity, the upper value of diversity indicators is attained when all industries in a region have equal employment size. For relative indicators, the upper value of specialization indicators will be obtained when a region is entirely specialized in one industry, while every other region has different specialized industries. In the case of measuring diversity, when each region has the same economic structure as the reference group, the indicator will show the upper boundary. To reasonably compare the economic structures of regions, the boundaries have to be independent from the number of sectors in the regions (Combes & Overman, 2004). However, in reality, the boundaries can be changed by the number of industries (i.e., Entropy index). Therefore, when comparing economic structures among regions, it should be noted that the number of sectors might affect the boundaries of structure indicators.

Classification of industries

The empirical results of measuring economic structure can be affected by splitting an industry into many sub-industries or merging a few sub-industries to one larger industry (Palan, 2010). In terms of economic structural indicators, when splitting one industry into a few small industries, the level of the absolute diversity indicator will increase or the value of the absolute specialization indicator will decrease. However, if a few small industries are merged to one larger industry, the absolute diversity will decrease or the absolute specialization will increase. This industrial classification can be a serious issue if the classification level varies systematically by the types of large economic sectors. Furthermore, the changes in industrial classification over time might influence the results of measuring economic structures in regions (Palan, 2010). Specifically, Krugman (1991) argued that, because the economic sectors of information and communication technologies (ICT) tend to be more finely classified than other economic sectors such as textiles, the specialization level of ICT industries can be underestimated while the diversity level can be overestimated.

Number of sectors or industries

For absolute indicators, adding an industry or sector with negligible employment share should have only an ignorable effect on the results of measuring economic structures in regions (Hannah & Kay, 1977). Similarly, for relative indicators, adding an industry or sector with zero or a very small employment share in one specific region, the average of the reference group should have no impact on the results of measuring economic structures in that specific region.

4.2 Evaluating Economic Structure Measures

4.2.1 Various Economic Measures

In this section, I evaluate the five most frequently used normative economic structure indicators – the Hirschman-Herfindahl index, the entropy index, the Ogive index, the national average index, and the Krugman specialization index – using the six criteria explained in Section 4.1.

Hirschman-Herfindahl index

The Hirschman-Herfindahl (HH) index, introduced and developed by Herfindahl (1950) and Hirschman (1964), has usually been applied in the field of industrial economics (Scherer & Ross, 1990). In industrial economics, the HH index is used to measure market concentration or to particularly inspect an oligopoly or cartels (Clarke, Davies, & Waterson, 1984; Hannah & Kay, 1977; Tirole, 1988). Additionally, in terms of economic structure, the HH index is also applied to measure the specialization level of economic structures (Drucker, 2011; Izraeli & Murphy, 2003; Mizuno et al., 2006). The HH index is simply calculated by summing up the squared values of each industry's share in one region.

$$H_i = \sum_{n=1}^{N} \left(\frac{e_{ni}}{e_i} \right)^2$$

where e_{ni} is the employment of an industry or sector n; e_i is the total employment; N is the total number of sectors or industries in region i. Hence, the greater the value of the HH index, the less diversified or more specialized is the regional economy. Because of a positive relationship between the indicator and the level of specialization, it is more frequently used to measure the level of specialization in empirical analysis.

The HH index is an absolute indicator because it is constructed irrespective of the economic structure in other regions. In addition, the HH index is calculated based on the uniform distribution of employment among sectors or industries in a region. So, the lower boundary $(H = \frac{1}{N})$ is attained when all industries have the same employment size while the upper boundary $(H = 1)$ is reached when all the employment is only concentrated in one industry. Hence, the value of the HH index is increased when employment is more concentrated in a limited number of sectors, but decreases with an increase in the number of sectors.

For other evaluation criteria, the HH index satisfies the axiom of anonymity because the results of calculating the HH index are independent of the order of industries or sectors. Also, the HH index satisfies the axiom of progressive transfer in that the transference of employment from a small to a large economic sector increases (decreases) the level of specialization (diversity) while shifting employment from a specialized industry to a less specialized one decreases (increases) the level of specialization (diversity). In addition, while splitting one industry into a few sub-industries decreases the value of the HH index, merging a few small industries increases the HH index. Adding an industry with negligible employment share hardly affects the results of calculating the HH index.

Entropy index

The entropy index was first used to measure racial diversity by using informational concepts. The basic idea of this index is that the value of entropy increases when the elements, which compose one specific system, become more diversified (Theil & Finizza, 1971). The entropy index can be classified into two types: – absolute and relative.

Absolute entropy index

The absolute entropy index is widely used in measuring both income distribution (Cowell, 1995) and economic structure (Aiginger & Davies, 2004; Attaran, 1986; Attaran & Zwick, 1987; Frenken et al., 2007; Kort, 1981; Malizia & Ke, 1993; Smith & Gibson, 1988; Trendle, 2006). The absolute entropy index of region *i*, E_i, is calculated by the following procedure:

$$E_i = \sum_{n=1}^{N} S_n \ln(\frac{1}{S_n})$$

where S_n is the absolute employment share of industry n, and N is the total number of industries in region i. Thus, this index indicates the upper boundary ($E = \ln(N)$) when employment is evenly distributed across all industries in a region while it reaches the lower boundary ($E = 0$) when all employment is concentrated in one specific industry. The calculation results of the absolute entropy index are independent of the sequential order of sectors. Additionally, the absolute entropy index satisfies the axiom of progressive transfer. For the criterion of industrial classification, the value of the absolute entropy index is increased by splitting one industry into a few sub-industries while it is also decreased by merging a few small industries into one large one. Moreover, adding an industry with an ignorable employment share (quite close to zero) only causes a negligible effect in the results.

Relative entropy index

The relative type of the entropy index is also used to measure both diversity and specialization in economic structure (Brülhart & Traeger, 2005; Ezcurra & Pascual, 2007). While the absolute entropy index is based on the benchmark of uniform distribution of employment, the relative entropy index is calculated using the dissimilarity in the economic structure of a region compared with the average economic structure of the regions in a reference group. Hence, if the economic structure in a region is more similar to the average economic structure of the regions in a reference group, the value of relative entropy index is smaller. This smaller value of the relative entropy index indicates a higher level of diversity or lower level of specialization. The calculation process for this indicator is:

$$E_i = \frac{1}{N}\sum_{n=1}^{N}\frac{S_n}{\overline{S_n}}\ln\left(\frac{S_n}{\overline{S_n}}\right)$$

where S_n is the employment share of industry n in region i, $\overline{S_n}$ is the average of employment shares of industry n of regions in the reference group, and N is the total number of industries. Additionally, the relative entropy index fulfills both the axiom of anonymity and the axiom of progressive transfer.

Furthermore, as in the case of the absolute entropy index, adding an industry with a negligible employment share only adds an ignorable effect to the results of the relative entropy index. However, the relative entropy index has a problem in defining the upper boundary value. Theoretically, because the relative entropy index is a relative indicator, the value will reach the upper boundary if the employment in a region is completely concentrated in one specific industry while the average of employment shares of a reference group indicates $\frac{1}{N}$ for all industries. In contrast, the lower boundary is obtained when the economic structure of a region and the average economic structure of a reference group are identical. However, in practice, the value of the relative entropy index from the upper boundary case – the employment in a region is completely concentrated in one specific industry or sector while the average of employment shares of a reference group indicates $\frac{1}{N}$ for all industries – mathematically indicates negative infinity while the minimum value of the relative entropy index is zero. Thus, the value (zero) from the lower boundary condition is not actually the minimum value of this relative entropy index. This is because if the number of industries which are less specialized than the reference group is larger than the number of industries which are more specialized than the reference group, the relative entropy index might indicate a negative value. For example, if the employment share distribution of region A and the distribution of average employment shares of the reference group with five industries are:

$$ED_{region\ A} = (S_1 = 0.2; S_2 = 0.29; S_3 = 0.1; S_4 = 0.28; S_5 = 0.13)$$

$$ED_{reference} = (S_1 = 0.2; S_2 = 0.3; S_3 = 0.1; S_4 = 0.25; S_5 = 0.15)$$

then the value of the relative entropy index is about -0.008. In this case, while two industries, 2 and 5 in region A, are less specialized than the reference group, only Industry 4 is more specialized than the reference group.

In addition, the relative entropy index has another problem in producing distorted results. Because all deviations of the economic structure between one specific region and a reference group are not evenly weighted, the level of diversity or specialization can be erroneously perceived and this misperception can consequently lead to a misleading conclusion (Palan, 2010). Suppose the employment share distribution of region A and the distribution of average employment shares of the reference group with five industries are:

$$ED_{region\ A} = (S_1 = 0.2; S_2 = 0.25; S_3 = 0.2; S_4 = 0.25; S_5 = 0.1)$$

$$ED_{reference} = (S_1 = 0.2; S_2 = 0.3; S_3 = 0.1; S_4 = 0.25; S_5 = 0.15)$$

The employment shares of industries 1 and 4 are identical whereas industries 2, 3 and 5 have deviations. The value of the relative entropy index for this case is about 0.193. If the above employment share distributions for both region A and the reference group are changed to the following:

$$ED_{region\ A\_changed} = (S_1 = 0.1; S_2 = 0.35; S_3 = 0.3; S_4 = 0.15; S_5 = 0.1)$$

$$ED_{reference\_changed} = (S_1 = 0.1; S_2 = 0.4; S_3 = 0.2; S_4 = 0.15; S_5 = 0.15)$$

then the employment shares of industries 1 and 4 are still the same. Moreover, the deviations of industries 2, 3 and 5 between region A and the reference group are also identical, as in the former case. However, the value of the relative entropy index for this case is about 0.044. This shows that, although the deviations of economic structure between one specific region and a reference group are identical, the value of the relative entropy index can vary because deviations are not equally weighted. Additionally, the relative entropy index yields irrational values when splitting or merging industries. Regardless of the current economic structure in a region, dividing one large industry into many small industries increases the level of economic specialization calculated by the relative entropy index whereas merging a few small industries into one large industry decreases the level of economic specialization. This pattern does not fulfill the general relationship between diversity (specialization) and the level of industrial classification (Brülhart & Traeger, 2005).

Ogive index

The Ogive index was first introduced by Tress (1938) to investigate economic diversity. After that, the Ogive index has been popularly used in measuring economic structure in regions or countries (Attaran & Zwick, 1987; Bahl, Firestine, & Phares, 1971; Brewer & Moomaw, 1985; Brewery, 1985; Hackbart & Anderson, 1975; Kort, 1981; Wasylenko & Erickson, 1978). It is based on the case that all industries in one region are evenly distributed in their employment sizes. So, the Ogive index in region *i*, O_i , is mathematically calculated by summing up the ratio difference between the actual share of industry and the share of industry in an evenly distributed case. So, it uses the uniform distribution employment in a region as a benchmark economic structure. The calculating equation is:

$$O_i = \sum_{n=1}^{N} N\left(S_n - \frac{1}{N}\right)^2$$

where N is the total number of sectors or industries and S_n is the employment share of sector *n*. Hence, if the economic structure in a region is different from the benchmark economic structure of uniform employment distribution among industries, that economic structure is considered to be more specialized. In this context, when the economic structure of a region is perfectly diversified (all industries in a region indicate the same employment shares), the Ogive index reaches its lower boundary of zero. In contrast, the upper boundary $(N-1)$ of the Ogive index can be obtained if all the employment is only concentrated in one industry. Because of squared term in the equation, the industries with a larger deviation from the uniform distribution are relatively more weighted in the process of calculating the Ogive index. Hence, there is a risk in that the level of diversity can be overestimated by this index. To deal with this overestimation, Jackson (1984) used the absolute value of deviation instead of the squared deviation.

In addition, the Ogive index satisfies the axioms of anonymity and progressive transfers. For the classification of industries, while splitting one industry into a few sub-industries decreases the level of specialization measured by the Ogive index, merging a few small industries increases the level of diversity. Moreover, adding an industry with zero or ignorable employment shares seriously affects the results of calculating the Ogive index because adding an industry simultaneously affects the benchmark economic structure ($\frac{1}{N}$), regardless of the amount of added employment shares.

National average index

The national average index employs the national economic structure as the benchmark (Siegel, Johnson, & Alwang, 1995). If the economic structure in one region is different from the national level, the economic structure in that region is considered more specialized. The national average index is also used in a great deal of empirical research to measure economic structure in regions (Brewer & Moomaw, 1985; Brewery, 1985; Jackson, 1984; Kort, 1981; Lynch, 1979; Sherwood-Call, 1990). The value of this indicator is the sum of the ratio difference between industry's share in total industries in one region and industry's share in total industries in a nation. The calculation process for the national average index, N_i, is:

$$N_i = \sum_{n=1}^{N} \frac{\left(S_n - \overline{S_n}\right)^2}{\overline{S_n}}$$

where N is the total number of sectors or industries; S_n is the regional employment share of sector *n*; $\overline{S_n}$ is the national employment share of sector *n*. The lower boundary of the national average index (0) is obtained if the economic structure in a region is the same as the national economic structure. Otherwise, when all employment in a region is concentrated in one specific industry indicating the smallest employment share at the national level, the national average index converges towards its upper boundary, which is the inverse of the smallest employment share. Moreover, as in the case of the Ogive index, the level of diversity can be overestimated. This is because the squared term in the equation gives more weight to the industries with a larger deviation from the national economic structure in the process of calculating the national average index.

In addition, for other criteria for economic structure indicators, the national average index satisfies both the axioms of anonymity and progressive transfers. For the classification of industries, splitting (merging) industries does not necessarily increase (decrease) the level of diversity (specialization) because the value of the national average index is determined by the deviation of economic structures between a region and the national level. Hence, splitting one large industry into a few sub-industries can maintain or increase the level of specialization. Furthermore, adding an industry with zero or a negligible employment share hardly affects the level of specialization or diversity of the economic structure in a region.

Krugman specialization index

The Krugman specialization index (KS) is one of the most widely used specialization indicators. The KS index is induced by calculating the absolute deviation between the economic structure of one specific region and the economic structure of one benchmark region (Krugman, 1992) or the average economic structure of regions in a reference group (Longhi, Nijkamp, & Traistaru, 2004; Palan & Schmiedeberg, 2010). The process for calculating the KS index is:

$$KS = \sum_{n=1}^{N} \left| S_n - \overline{S_n} \right|$$

where N is the total number of sectors or industries; S_n is the employment share of sector *n* in a region; $\overline{S_n}$ is the average employment share of sector *n* in a reference group. The lower boundary of the KS index is zero when the economic structure in a region and the benchmark economic structure are identical. When the economic structure of a region deviates from the reference group, the KS index shows a higher value and the economic structure in that region is considered to be more specialized. In contrast, when all employment in a region is concentrated in one specific industry, which is least specialized in the reference group, the KS index will converge towards its upper boundary value of two. Moreover, as in the case of the national average index, changing industrial classification does not necessarily affect the level of diversity or specialization. For example, if some sub-industries in a region are more specialized than the reference group while other sub-industries in a region are less specialized than the reference group, merging these sub-industries may not affect the level of specialization in a region because the effects of over and under specialization can cancel each other out (Palan, 2010). In addition, the KS index fulfills both the axioms of anonymity and progressive transfer. Moreover, adding an industry with a zero or negligible employment share hardly changes the value of the KS index in a region.

Discussion

Between the absolute and relative indicators, the absolute indicator seems to be more suitable for this dissertation. When applying the relative indicators, the level of specialization or diversity is determined by the relative portions of industries to the industrial shares in the benchmark or reference economic structure (e.g., national economic structure or average economic structure of regions in the reference group). However, in this case, it is difficult to discern the effects of diversity on stabilizing the effects of macro-economic fluctuation using the relative indicators. For instance, when applying the national average index, this relative indicator generally indicates a higher level of diversity if the economic structure in a region is more similar to the national average economic structure. Hence, in practice, there is a risk that the effect of diversity on reducing economic instability caused by national economic fluctuations might hardly be captured by using the national average index. Because a high level of diversity simply reflects the fact that the economic structure in a region more resembles the national economic structure and the weak points of the economic structure in that region are also similar to those of the national economic structure. So, when one specific sector in the national economic structure is severely affected by some external shock, the impact from this shock can also be significantly observed in the economic structure of that region indicating a high level of diversity by this relative structure indicator. Therefore, even if using the relative structure index can clearly show the comparative advantages of a region's economic structure in relation to other regions, the relative structure indicators are still limited in that they cannot properly reveal the effects of diversity on reducing the instability. Hence, if other structure indicators are simultaneously employed to properly capture the effects of the regional comparative advantages, using the absolute structure indicators seems to be a better option for comprehensively investigating the role of economic structure in both economic growth and stability.

More specifically, as presented in Table 4.1, among the absolute indicators, both the Hirschman-Herfindahl index and the entropy index seem superior. This is because that they are easy to calculate and they satisfy more evaluation criteria than other indicators. However, when employing the Hirschman-Herfindahl index, it should be noted that the squared term in the equation can give more weight to the industries with large employment shares. Therefore, this dissertation will apply the entropy index as a basic measure for overall economic structures in regions.

Table 4.1 Evaluation of the Normative Structure Measures

	Absolute /Relative	Anonymity	Progressive Transfer	Industrial Classification	Adding one industry with ignorable employment share	Upper boundary	Lower boundary
HH	A	S	S	S	S	1	1/N
Absolute Entropy	A	S	S	S	S	ln(N)	0
Relative Entropy	R	S	S	NS	S	ln(N)	0
Ogive	A	S	S	S	S	N-1	0
National Average	R	S	S	NS	S	$1/S_{least}$	0
Krugman	R	S	S	NS	S	2	0

(Note: A-Absolute[9]; R-Relative[10]; S-Satisfy; NS-Not Satisfy; N-the number of industries; S_{least} - the smallest industrial share in a reference group)

[9] The absolute indicators measure economic structure using the distribution of the overall employment among all the industries or sectors in a region.
[10] The relative indicators measure economic structure based on the deviation of the economic structure of a region from the economic structure of the nation or the average economic structure of the reference group.

4.3 Multiple Specializations Indicator

4.3.1 Background

The notion of multiple specializations was theoretically introduced by Malizia and Ke (1993):

> *"Diversity is not simply the absence of specialization. Among metropolitan areas of sufficient size, diversity reflects the presence of multiple specializations. These specializations can be the source of competitiveness, as well as compensate for one another when business cycles or external shocks occur" (p. 223).*

Theoretically, multiple specializations in the economic structure can promote both economic growth and stability at the same time. For growth, according to Jacobs (1969), the characteristic of diversity in multiple specializations can positively affect the economic growth and innovations through the complementary effects of knowledge spillovers from diversified sectors. In addition, the effects from specialization in each sector are also expected to be positively associated with economic growth through knowledge accumulation (Saxenian, 1994). On the other hand, the concept of multiple specializations in an economic structure is also positively related to enhancing economic stability. The effects from severe fluctuations can be offset by the nature of diversity in multiple specializations (Gilchrist & St. Louis, 1991). Moreover, because the economic structure of multiple specializations is more likely to have relatively more specialized sectors, when some sectors are affected by fluctuations, it is expected that the negative effects in those sectors are compensated for by extra growth from other specialized sectors.

However, from empirical perspectives, there has been no empirical indicator to measure the concept of multiple specializations in the economic structure. To consider the effects of multiple specializations, some studies employ multiple LQs to capture the effects of specialization in a few selected industries (Glaeser et al., 1992; Mizuno et al., 2006). However, as previously mentioned (See section 2.1), considering the effect of specialization in selected industries is limited because the types of specialized economic industries, which indicate the comparative advantage for regional economic development, can be different by regions. So, measuring the level of specialization in the same economic sectors in all regions might lead us to ignore the effects of other specialized sectors that are not selected.

In addition, as mentioned by Malizia and Ke (1993), in regions or metropolitan areas with sufficient skilled or educated laborers and advanced technologies, the level of diversity measured by some normative indicators such as absolute entropy or the Hirschman-Herfindahl index may implicitly and indirectly indicate multiple specializations. This is because, at a fixed industrial classification level, an economic structure with multiple specializations can also be shown as some type of diversified economic structure. Specifically, in terms of overall economic structure, if many industries or sectors in a region are specialized with similar employment sizes, the diversity level of this economic structure will indicate a high value. However, in contrast, a high level of diversity at this fixed industrial level does not necessarily indicate multiple specializations. This is because there is no way to discern whether some high diversity level is based on multiple specializations. Therefore, there is a need to develop an empirical indicator to collectively measure multiple specializations and examine the effects of multiple specializations on regional economic performance.

From the perspectives of development policies, we may find another reason to investigate the concept of multiple specializations in regional economic structures (Dissart, 2003). Since the mid-1990s, a new trend in economic development, the so called "third-wave economic development," has emerged. This new trend has brought about a shift in the main target of local economic development from firm-based strategies to a regional system-based program (Bradshaw & Blakely, 1999). For instance, in the past, local governments tried to recruit large size firms or corporations, or their head offices to extend their economic bases. However, the third-wave economic development policies are rather focused on building a firm- or industry-friendly complex. The most representative example of this recent development strategy by regional system-based policy is Porter's cluster. In Porter (1998), a cluster is defined as: "… geographical concentrations of interconnected companies and institutions in a particular field" (p. 78). In this sense, the cluster itself is a highly specialized unit of economic structure. Moreover, it is noted that, when local governments implement the strategy for fostering clusters, they tend to build various types of clusters simultaneously to diversify their economic bases (Feser, 1998). Additionally, these newly constructed clusters have tended to be located close together, usually in high density population areas due to the various positive externalities from agglomeration economies (Siegel et al., 1995). As a result of cluster development, the economic structure in a region is expected to indicate multiple specializations based on various clusters. Hence, there is need to examine the effect of this new trend on regional economic performance.

4.3.2 Measuring Multiple Specializations

The development of an empirical measurement for multiple specializations starts from the specialization indicator for each sector or industry. The specialization of one specific sector or industry is most frequently measured by a Location Quotient (LQ) (Malizia & Feser, 1999). The LQ indicates the portion of industry employment in a region relative to the national share of that industry and therefore it is calculated by the following:

$$LQ_n = S_{ni} / NS_n$$

where S_{ni} is the employment share of sector *n* in region *i* and NS_n is the employment share of sector *n* at the national level. In the empirical analyses, when the LQ value of one industry in a region is larger than one, that industry is normally regarded as a specialized industry in relation to the national level.

The Multiple Specializations Indicator (MSI) proposed in this dissertation is computed by using the LQs of industries in a region. The process of obtaining the MSI consists of two simple steps. First, the total number of specialized sectors or industries which have LQ values greater than one is counted. Second, this total number of specialized sectors is divided by the total number of all sectors with non-zero employment in a region. In short, the MSI is the proportion of sectors or industries which are regarded as specialized ones. Therefore the MSI of region *i* is calculated as:

$$MSI_1 = \frac{1}{N}\sum_{n=1}^{N} SP_n \qquad \text{where } SP_n \begin{cases} = 1\ if\ LQ_n > 1 \\ = 0\ otherwise \end{cases}$$

LQ_n is the LQ of industry n; N is the total number of all industries in region i. Considering the above calculation process, the MSI indicates the proportion of all sectors that have the values of LQ over one.[11] Because the MSI focuses on the specializations of multiple sectors in an overall economic structure, not the level of specialization or diversity of each individual industry or sector, each region will have one MSI value. Moreover, although the MSI indicates the proportion of specialized industries in a region, the MSI is a relative structural indicator because the level of specialization in each industry is calculated based on the relative employment share of each industry to the national share. For other criteria for structural measures, because the MSI represents the proportion of industries indicating an LQ value greater than one, the MSI reaches the maximum value of one if the LQs of all the industries in a region are greater than one. In contrast, the minimum value of the MSI, zero, is obtained when there is no relatively specialized industry in a region. In addition, the MSI fulfills the axiom of anonymity. The order of calculating the LQ of each industry does not affect the level of the MSI. Moreover, when one industry with an ignorable employment share is

[11] Instead of using the absolute cut-off LQ value of 1 for specialized industries, the different types of relative cut-off values can be applied for classifying specialized industries. For this purpose, using the distribution of LQs of each 3-digit industry across all regions, I calculated the bootstrapped 75 an 80 percentile LQ values for each industry. Then, instead of the LQ value of 1, I used these percentile values as cut-offs for classifying specialized industries (However, I used the LQ value, 1, for the cases that the percentile values are less than 1). As a result, most of the models using the MSI based on these cut-off values also produced substantially similar results for overall models. However, in the results of panel models based on the short-term periods indicating different macroeconomic situations, the MSI with a cut-off value of 80 percentile showed insignificant effect on employment instability.

added to the economic structure in a region, the MSI will be decreased.[12] This is because the added industry with a zero or ignorable employment share might not affect the specialization level but will increase the number of industries in a region. Moreover, because the value of the MSI is calculated by the number of specialized industries, not by the degree of their relative specializations, the MSI does not satisfy the axiom of progressive transfer. As previously mentioned, the MSI is a relative indicator because the MSI counts the number of industries based on whether the industries are relatively specialized.

Comparing the MSI with other normative structure indicators, the most remarkable attribute of the MSI is that, by using the MSI, both diversity and specialization can be considered at the same time. For example, as repeatedly mentioned, the normative indicators regard the high level of specialization in the overall economic structure as the less diversified structure. The value of these normative indicators is usually determined by the employment distributions among the industries and the number of industries or sectors in a region. However, the value of the MSI is calculated by the number of specialized sectors. More specifically, suppose the employment share distributions of five industries in regions A, B, and the nation are as indicated in Table 4.2:

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[12] If, instead of the total number of 3-digit industries with non-zero employment, the MSI is calculated based on the total number of all 3-digit industries including zero employment, the value of MSI will be maintained when one industry with a zero or ignorable employment share is added. This is because the number of specialized industries across regions will be divided by the same denominator (the total number of all 3-digit industries listed in County Business Pattern) across regions. So, I ran the models including this MSI based on the absolute number of total industries. These models yielded substantially similar results.

Table 4.2 Employment Share Distributions I

	Nation	Region A	Region B
Industry 1	0.1	0.2	0.1
Industry 2	0.05	0.1	0.5
Industry 3	0.2	0.1	0.1
Industry 4	0.1	0.5	0.1
Industry 5	0.3	0.1	0.2

Assuming that the level of total employment sizes of both regions A and B are the same, when measuring the level of diversity (specialization) by the absolute indicator the measuring results for both regions A and B will be identical. However, in region A, there are three specialized industries in its economic structure while region B has only one specialized industry. So, although the overall economic structures are similarly measured by the absolute indicators, in these cases we cannot say that these two economic structures are identical because the levels of relative industrial specializations in these two regions are quite different. However, unfortunately, by using the absolute indicator, the level of specialization in relation to the national level or other reference group cannot be captured. However, the MSI allows us to overcome this limitation. Specifically, if we apply the MSI in these cases, the MSI for region A is 0.6 and the MSI for region B is 0.2. The higher value (0.6) for region A reflects the fact that the number of specialized industries in region A is larger than in region B.

In addition, the MSI can also overcome the limitations of the empirical approach using relative structure indicators. When measuring the overall economic structure, the relative structure indicators usually consider the relative specialization because they are calculated based on comparing the economic structures between one specific region and a nation or reference group. However, by using the relative structure indicators, it is impossible to discern whether the level of specialization of the overall economic structure is based on one extremely specialized industry or a group of a few moderately specialized industries. For instance, suppose the employment share distributions of five industries in regions A, B, and the nation are as indicated in Table 4.3:

Table 4.3 Employment Share Distributions II

	Nation	Region A	Region B
Industry 1	0.2	0.225	0.19
Industry 2	0.2	0.225	0.17
Industry 3	0.2	0.225	0.17
Industry 4	0.2	0.225	0.18
Industry 5	0.2	0.1	0.29

In both regions A and B, the levels of specialization measured by the Krugman specialization index are identical at 0.18. However, the specialization level of overall economic structure in region A is based on four specialized industries whereas the specialization level of region B mostly comes from industry 5. In other words, the level of specialization in region A is based on a more diversified economic structure than in region B. The level of diversity among the specialized industries cannot be grasped by using the relative indicator. However, if we apply the MSI in these cases, the MSI for region A is 0.8 and the MSI for region B is 0.2. The higher value of MSI in region A implies that the level of overall specialization in region A is based on more multiple industries than in region B. Thus, using the MSI also helps us understand the differences in the levels of diversity embedded in the effect of specialization.

However, it is impossible to infer the form of overall economic structure by simply measuring the MSI. This is because the MSI focuses only on the level of diversity among specialized sectors not the overall economic structure. Therefore, in order to comprehensively understand a variety of types of economic structures in regions, the MSI should be used with other structure measures. In other words, the MSI is a kind of complimentary index, which can help the analyst to consider the effect of the multiply specialized structures which are hardly detected by the other overall structure indicators.

In addition, the MSI has the same limitations as using the LQ because it is calculated based on the LQs of industries in a region. The LQ is a useful indicator for identifying the relatively concentrated industries in a region because it compares the fraction of regional employment in an industry to the share of national employment in that industry. However, the approach using the LQ is somewhat limited due to the following reasons. First, the LQ is very sensitive to the size of a population or employment in regions (Ejermo, 2005). The industries or sectors in the region with small employment size may result in distorted LQs. For example, the manufacturing industry inherently tends to have a larger employment size than other industries, regardless of its contribution to economic growth. So, if a region with only a few thousand total employment size has more than 500 employees in the manufacturing industry, the LQ of the manufacturing industry in that region will indicate a high value. However, we cannot easily say that this high value of the LQ in the manufacturing industry really represents a competitive specialization of the manufacturing industry. Hence, when making inferences from the results of measuring the LQs, the analyst should consider the size of the region's economy. Second, the LQ is also sensitive to the level of aggregation used in industrial classification (Wagner, 2000). For instance, an industry classified by a 2-digit NAICS code may indicate a LQ less than one; however, when applying a 4-digit NAICS code, that industry can have an LQ greater than one. The final limitation in using the LQ is that the specialization effect of an industry can arise from the absolute size of that industry not the relative size of that industry. Specifically, Duranton and Puga (2003) claimed that the absolute size of an industry might more reflect the effects of the specialization of that industry. Hence, although one industry reveals an ignorable share of one region's overall employment, that region might demonstrate a successful cluster of that industry (Beaudry & Schiffauerova, 2009). For this reason, the recent articles emphasizing the absolute size of concentrated industries argue that the level of specialization measured by the LQ might be systemically underestimated for large metropolitan areas with a huge employment size (Drennan, Larsen, Lobo, Strumsky, & Utomo, 2002). Thus, when determining whether an industry is really specialized, the value measured by the LQ is just one piece of the information. Therefore, when using the MSI, which is based on multiple LQs, the analysts should consider the total number of firms and employment in a region and the level of industrial classification used in the analysis.

Moreover, the MSI is also limited in that it cannot consider the degree of specialization in each industry. In the process of computing the value of the MSI, if the LQ of one specific industry is larger than one, the MSI counts one for that industry, regardless of how much the LQ differs from the cutoff value, one. Specifically, suppose the employment share distributions of regions A, B, and a nation with five industries are indicated as in Table 4.4:

Table 4.4 Employment Share Distributions III

	Nation	Region A	Region B
Industry 1	0.2	0.25	0.45
Industry 2	0.2	0.25	0.45
Industry 3	0.2	0.16	0.03
Industry 4	0.2	0.17	0.03
Industry 5	0.2	0.17	0.04

In both regions A and B, the MSIs are indicated as identical at 0.4 and these MSIs are based on two specialized industries 1 and 2. However, the levels of the specializations of industries 1 and 2 in region A are higher than in region B. But the MSI cannot discern this difference in the level of specializations in the industries in the regions. The effects of main industries or sectors should be considered as types of individual factors that can influence the economic performance in regions. In other words, the MSI should be used in conjunction with other structure indicators such as entropy or the Herfindahl index. Hence, in this study, I use the MSI with the entropy indicator for measuring the overall economic structure in regions.

4.4 Concluding Remarks

This review chapter presented various empirical measurements of economic structure and evaluated their pros and cons for empirical study. Additionally, a new indicator for measuring multiple specializations was also introduced and discussed. The main implication from the present chapter is that the research about economic structure or its related topics can significantly depend on how the economic structure is measured and there is no critique free measurement for economic structure. Moreover, it is a risky expectation that one variable can be a panacea for investigating various aspects of economic structure (Dissart, 2003; Nissan & Carter, 2010; Siegel, Johnson, et al., 1995; Wagner, 2000). Therefore, to appropriately use the structure indicators, it is important to fully understand the strengths and limitations of the used indicators.

CHAPTER V

RESEARCH METHODS

5.1 Study Design

5.1.1 Two Approaches

The main objective of this dissertation is to investigate how economic structure affects regional economic performance. Regional economic performance is measured by both economic growth and stability. As previously mentioned in Chapter 4, the effects of economic structure are measured by two indicators – the entropy index and the multiple specializations indicator. Thus, to more specifically achieve the main objective of this research, the following four research questions were previously proposed:

1. Which economic structure is the most efficient for achieving high economic growth?

2. Which economic structure can secure regional economic stability?

3. Which economic structure helps regions accomplish both economic growth and stability simultaneously?

4. Do the relationships between economic structure and performance, which are assumed in the above research questions and hypotheses, hold for different macro-economic situations?

To investigate the first three research questions, two regression models – one has economic growth as its dependent variable and another has economic instability as its dependent variable – were estimated.

To address the fourth research question, I generated four cross-sectional data sets by dividing the overall research time period into four sub-time periods based on macro-economic situations. After this, I pooled the four cross-sectional data into one data set for panel models. Using the panel models allowed me to capture the effects of economic structure through the four different time periods as well as differences in growth and stability in economic booms and busts, within one statistical model. I estimated two panel models, one had economic growth as its dependent variable and the other had economic instability as its dependent variable.

5.1.2 Study Area and Temporal Scale

Study area

As depicted in Figure 5.1, the unit of analysis in this study was the 353 Metropolitan Statistical Areas (MSA) in the lower contiguous 48 states, which are defined by the Office of Management and Budget.[13] The MSAs were the most frequently used unit of analysis in previous literature because they resemble a functional economic unit. Various geographic scales have been used as geographical units of analysis in previous studies. Such studies attempted to legitimize their selection of observational units by many different reasons such as a policy making unit or data availability. For instance, Wagner & Deller (1998) used state as a unit of analysis because state is a critical unit for many

[13] The OMB (2003) describes the general concept of MSAs as "a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core" (OMB, 2010, p. 37249). Specifically, the areas which have at least 50,000 inhabitants in one urbanized area are designated as one metropolitan statistical area.

development policies and data were available at the state level. Krugman (1992) pointed out that state is an inappropriate unit for regional economic research due to the discordance between an effective economic market and political unit. Similarly, using the county level as an observational unit is also inappropriate because many counties in rural areas do not properly reflect the regional economic functions. However, the MSAs are composed of the core counties and qualifying surrounding counties based on their economic linkages. Therefore, in terms of economic function, the MSAs are less arbitrary observation units than other geographical units.

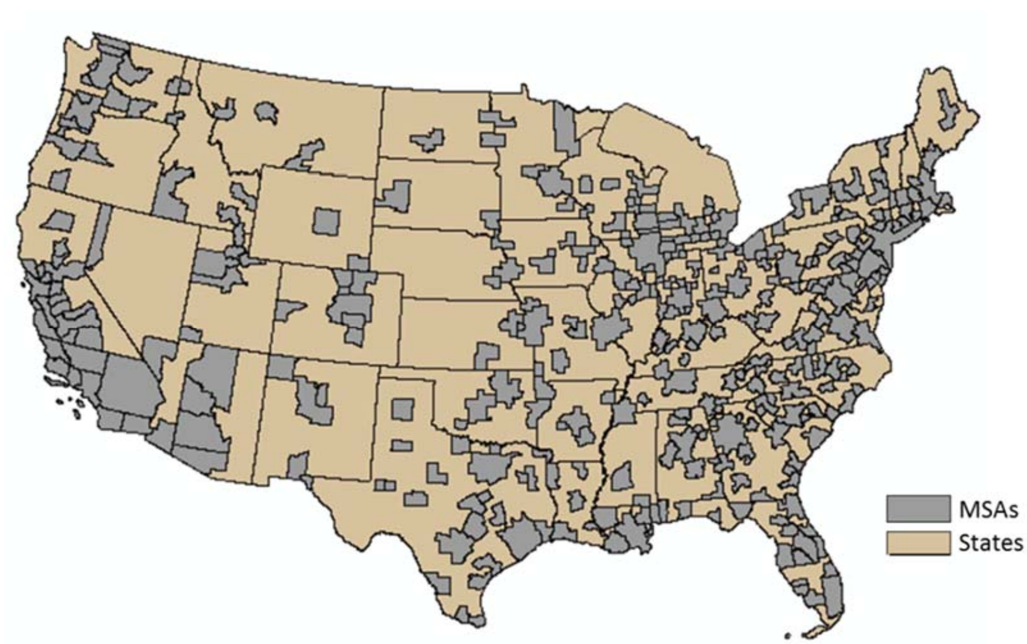

Figure 5.1 Metropolitan Statistical Areas[14]

[14] The map in Figure 5.1 is depicted by Albers Equal Area Conic projection which is frequently used in the U.S. and other large areas with a larger east-west than north-south extent (Bugaevskij & Snyder, 1995).

More specifically, there were a total of 359 MSAs in the lower contiguous 48 states in 1998, the initial time point of this study. Among them, six MSAs – Bristol, Florence, Fort Walton Beach-Crestview-Destin, Sarasota-Bradenton-Venice, Vero Beach, and Weirton-Steubenville – were excluded because their including counties were changed during the research period from 1998 to 2010. Hence, only 353 MSAs were used in this study.[15]

Temporal scale

The time span of this research is the 12 years from 1998 to 2010. This is because the *County Business Pattern* (CBP), the main dataset used to construct economic structural indicators in this study, started to use the North America Industry Classification System (NAICS) in 1998. Before that, the CBP was based on the Standard Industrial Classification (SIC), which is an outdated industrial categorization system. Because there is no exact matching bridge between the SIC and NAICS systems, it is difficult to transform SIC-based data to NAICS-based. Therefore, I only utilized data from 1998 onward, which have been consistently reported on the basis of NAICS.

Moreover, to test the consistency of the effects of economic structure on economic performance during varying macro-economic situations, the overall time period from 1998 to 2010 was divided into four sub-time periods based on national level economic performance measured by the U.S. national unemployment rate (Figure 5.2).

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[15] There was a large shift in the definition of MSAs between 2002 and 2003. To deal with the inconsistency of the spatial unit, I used the 2003 MSAs definitions to aggregate all county-level data into MSA data for the 5 years from 1998 to 2002.

As depicted in Figure 5.2, the overall time span was divided into four sub-periods which consist of two boom periods – period 1 (1998-2000) and period 3 (2003-2007) – and two bust periods – period 2 (2000-2003) and period 4 (2007-2010)[16].

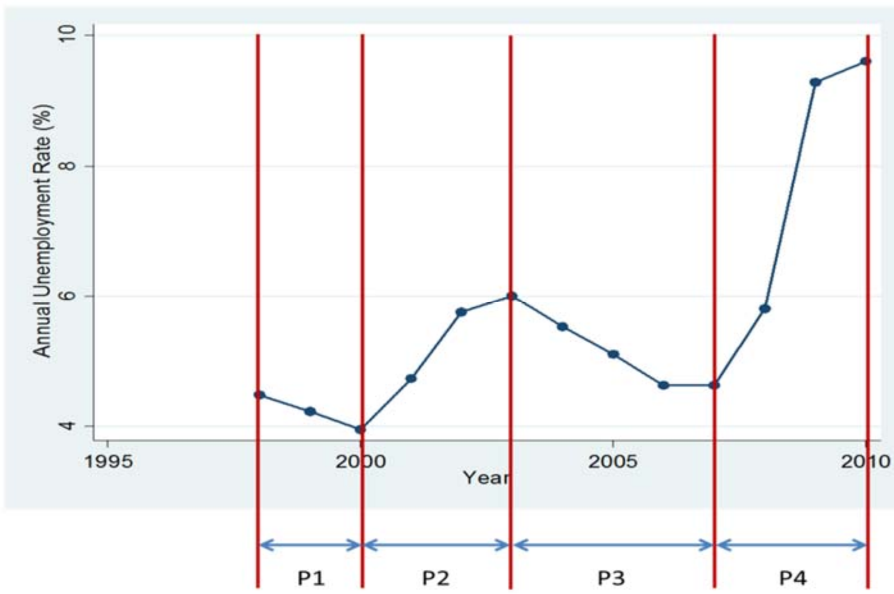

Figure 5.2 U.S. Annual Unemployment Rate (1998-2010)

[16] The starting year of period 4 (2007) is based on the clarification by National Bureau of Economic Research (Source: http://www.nber.org/cycles/cyclesmain.html)

5.2 Data and Measurements

5.2.1 Dependent Variables

As previously mentioned, in this study, I measured economic performances in terms of both growth and instability. This section discusses both measurements.

Economic growth

Economic growth is usually measured by simple quantitative differences or the change rates of economic outcomes between two time points. The frequently used indicators for economic growth include the growth rates of employment, wages, per capita personal income, or productivity. In this dissertation, I followed Wagner and Deller (1998) to measure economic growth in region *i*, EG_i, by the average of annual employment growth rates during the research time span. This measurement is calculated as:

$$EG_i = \frac{\sum_{t=2}^{T}\left[100 * \frac{E_{it} - E_{it-1}}{E_{it-1}}\right]}{T-1}$$

where E_{it} is the employment level in region *i* at year *t* and *T* is the number of total years.

Economic instability

According to Dissart (2003), the indicators for regional economic instability can vary by how they deal with the components of economic time series data – seasonal, trend, and cyclical. The economy in a region can fluctuate by seasonal events or attributes such as holidays, school calendars, or the weather, which is called seasonal economic instability

(Miron & Barsky, 1989). Additionally, the trend indicates a long-term movement or change in the overall level of economic time series (e.g., long-term growth or decline). The cyclical instability represents fluctuations or instability around the general economic trend (Zarnowitz & Ozyildirim, 2006). Theoretically, it is known that the effect of economic structure on reducing instability is mostly related to the cyclical component of economic instability (Kort, 1981). As mentioned in Chapter 4, if the economic structure in a region is absolutely diversified, even if there is one external shock in the national level economy, the cyclical instability caused by this shock can be easily smoothed by the diversified economic structure. So, the previous studies investigating the relationship between economic structure and instability have tried to isolate and measure the instability based on the cyclical component of an economic time series (Dissart, 2003; Kort, 1981). However, in spite of these efforts, many previous studies usually tended to ignore these various components of economic instability by using a simple variance-based statistic to measure instability (Brewer, 1985). As previously mentioned in Section 2.2, applying a simple variance-based statistic is seriously limited because the effects of natural economic trends cannot be measured by this simple variance statistic. In other words, it is impossible to discern whether some variations are caused by economic instability or the results of economic trends by using a variance-based indicator.

To overcome the above limitation, Kort (1981) developed an advanced indictor for measuring economic instability, which was called the regional economic instability (REI) index. I adopted this REI index to measure instability. The economic indicator studied is employment in regions. More specifically, using the REI index, employment instability is defined as the average deviation from the employment trend, divided by trend employment. The instability indicator for region *i*, $INSTAB_i$, is defined as the following:

$$INSTAB_i = \left\{ \sum_{t=1}^{T} \left[(E_{it} - E_{it}^{Tr}) / E_{it}^{Tr} \right]^2 / T \right\}^{0.5}$$

where E_{it} is the employment level in region *i* at month *t*; E_{it}^{Tr} is the predicted employment level from trend regression in region *i* at month *t*; *T* is the total number of months. The value of the REI index increases as the difference between the actual and predicted employment increases. In this study, this measure was calculated using monthly employment data during the research time span from 1998 to 2010. It should be noted that, to control for monthly seasonal effects, this study estimated the above trend regression with dummy variables for each of the months except December. The above technique teased out the cyclical component of instability from the trend and seasonal components. Because the cyclical instability was skewed, I performed a natural log transformation on the indicator before using it as the dependent variable in regression models.

Data for dependent variables

The Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA) both provide data on metropolitan employment. Although the BEA employment data has one advantage of including the self-employed as well as all employees (Drennan et al., 2002), using the BEA data is inappropriate for the purpose of this dissertation because the BEA produces employment data for MSAs only on an annual basis. The BEA does not allow the measurement of economic instability at more refined time scales such as quarter or month. Otherwise, the BLS publishes employment data at a higher frequency. There are two types of BLS employment data for MSAs, the Current Employment Statistics (CES) and the Quarterly Census of Employment and Wages (QCEW). The CES are extrapolated from monthly surveys of "about 145,000 businesses and government agencies, representing approximately 557,000 individual worksites."[17] In contrast, the QCEW are derived from "a quarterly count of employment and wages reported by employers covering 98 percent of US jobs, available at the county, MSA, state and national levels by industry."[18] While the CES immediately publishes detailed employment information, it is limited because it is based on a much smaller sample than the QCEW. Instead, the QCEW is published every quarter but it provides detailed monthly data for all the months in each quarter. So, in spite of quarterly frequency and a 3 to 4 month release lag time, a great deal of sample size in the QCEW makes it an accurate data source for investigating employment at various geographical levels. Hence, in this study, the dependent variables were constructed based on the QCEW data.

[17] http://www.bls.gov/ces/
[18] http://www.bls.gov/cew/

5.2.2 Independent Variables

Entropy index and multiple specializations indicator

The entropy index and multiple specializations indicator (MSI) are the two indicators for measuring economic structure. As mentioned in Section 4.2, the entropy index measures economic diversity. The value of the entropy index increases as employment becomes more evenly distributed across sectors. The MSI was previously discussed in Chapter 4. It captures the presence of multiple specialized sectors in an economy. The value of the MSI increases when more sectors in the economy become specialized. The MSI measures the diversity in the region's specializations.

In this study, when measuring the economic structure using the entropy index and the MSI, the values of these indicators were calculated based on the 3-digit level industries of NAICS. According to the meta-analysis by Beaudry and Schiffauerova (2009), the effect of diversity tended to be more represented when a more detailed industrial classification is applied. This is because many indicators used for measuring the level of diversity in overall economic structure (e.g., entropy or the Herfindahl index) are positively associated with the number of sectors. The number of sectors is more likely to increase when a more refined classification is used. For instance, Krugman (1991) argued that, using the same digit level of NAICS, the information and communication technologies (ITC) sector tends to be more finely classified than other economic sectors such as textiles. So, the diversity level of the ICT sector can be overestimated while the specialization level can be underestimated. On the other hand, when a coarse classification is applied, the indicators used to identify the specialization effect (e.g., Location Quotient or share of each sector) might also reflect the effect of the diversity of the low-digit industries in these specialized sectors. In other words, the effects of diversity embedded in the specialization effects are hardly discerned by the specialization indicators based on a broad classification level. So, the influence of specialization estimated by these measures can be inflated by these embedded effects of diversity. For these reasons, Beaudry and Schiffauerova (2009) suggested that the 3-digit (medium) level of industrial classification might be the level at which both the effects of specialization and diversity are compatible with each other, minimizing the concern about over- or under- estimating the effects. Therefore, in this dissertation, all indicators for measuring economic structure were calculated based on the 3-digit level of NAICS.[19]

Data for structural indicators

In order to obtain the employment data based on the 3-digit level industries of NAICS, the County Business Patterns (CBP) from the U.S. Census Bureau had to be employed. The CBP provides "annual statistics on the businesses with paid workers within the U. S. These statistics are on business establishments at the U.S. level and by state, county, metropolitan area, and zip code levels."[20] However, although the CBP provides the employment data by a detailed geography and industry level, about 60 percent of employment statistics in the CBP are censored due to confidentiality. Instead of providing actual numbers, the missing data is filled with employment flags which

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[19] See Appendix A.
[20] http://www.census.gov/econ/cbp/overview.htm

indicate only the range of employment size, and the CBP also provides the number of establishments which are classified into about 13 different employment size classes. The methods used by previous researchers to overcome this data suppression problem are roughly categorized into two types. The first type simply used the average between the minimum and maximum values of each employment flag (Porter, 2003). The second type estimated missing data by using midpoints of establishment size classes (Glaeser et al., 1992).

In this dissertation, the suppressed data in the CBP were estimated by using a geometric means of the minimum and maximum values of establishment size classes.

$$Geomean_n = \sqrt[2]{Upper\ bound_n * Lower\ bound_n}$$

where $Upper\ bound_n$ is the topmost value of establishment size n and $Lower\ bound_n$ is lowest limitation of establishment size n. So the geometric mean of establishment size n is calculated by the formula above. Using this, the final estimation of suppressed data for industry or sector i is:

$$Estimation_i = \sum_{n=1}^{N} Geomean_n$$

where N is the total number of employment size classes of sector or industry i.

Geometric mean is used because using the midpoints (the arithmetic mean) between the minimum and maximum values of establishment size classes tends to excessively overestimate employment. To more precisely identify the tendency of overestimation, I calculated the estimated values for non-missing observations by two estimation methods – using the arithmetic and geometric means – and compared the averages of deviations (non-missing observations – estimated values) between these two types of estimated values and the actual values of non-missing observations.

Table 5.1 Comparison of the Deviations between Two Estimation Methods Using Non-Missing Values, 2004

Deviations by Estimation methods	Average	Standard Deviation	Min	Max	# of Observations
Using midpoint	-292.54	3966.93	-891923	135873	159234
Using geometric mean	-76.39	1354.97	-238408	138417	

As indicated in Table 5.1, in 2004, the average of deviations by the midpoint indicates a much larger negative value than the average of deviations using the geometric mean. Also, considering the high standard deviation and large negative value of the minimum in the deviations by the midpoint estimation method, the estimation by the midpoint is revealed to be far more skewed to the left than the average of deviations using the geometric mean.[21] All these statistics imply that using the midpoint tends to bring overestimation for suppressed observations.

In addition, I used another method to check the tendency of overestimation by the midpoint method. Although there are many suppressed observations in the data set,

[21] These symptoms are commonly observed in other years.

the total employment numbers for each MSA is disclosed. So, the average of deviations between the actual total employment numbers and the aggregated estimated values for each MSA could be calculated by the two types of estimation methods. Table 5.2 shows the comparison between the averages of deviations between the actual total employment and the aggregated estimations by the two methods.[22]

Table 5.2 Comparison of the Deviations between Two Estimation Methods Using Non-Missing Values, 2004

Deviations by Estimation methods	Average	Standard Deviation	Min	Max	# of Observations
Using midpoint	-10603.88	25211.55	-265078.8	8970.1	361
Using geometric mean	-1970.68	5794.90	-42151.3	14969.7	

Similar to the first case, the average of deviations by the arithmetic mean estimation shows a larger negative value than the average of deviations using the geometric mean. Additionally, other statistics – standard deviations and the minimum and maximum values – also indicated that the suppressed data is much more overestimated by the midpoint estimation method. Considering the above two cases, using the geometric mean, which is always less than the arithmetic mean, can produce better estimates for the suppressed data in the CBP.

[22] I computed the aggregated estimation based on the 3-digit level of NAICS.

5.2.3 Control Variables

Competition

In addition to diversity and specialization, local competition, which is usually measured through regional economic structure, is one of the important factors for regional economic performance. Although Jacobs (1969) and Porter (1990) disagreed on whether diversification is the preferred economic structure for growth, they both admitted the importance of local competition for growth (Glaeser et al., 1992). Specifically, Jacobs (1969) believed that a high level of local competition can stimulate firms or industries to increase the speed of developing innovative skills or knowledge. Moreover, Porter (1990) argued that, even if many local competitors might slightly reduce the return from their innovative ideas, a relentless competition can increase the pressure to innovate and can lead firms or industries to adopt the innovations of others and to improve these innovations rapidly. Therefore, they concluded that this process of creating and adopting local innovations stirred by competition can finally result in economic growth. Thus, I also expect competition to be positively correlated with growth.

On the other hand, high competition may decrease regional economic stability. Because the level of market competition is directly associated with each firm's market power, firms can enjoy greater market power in less competitive market environments, whereas more competitive market conditions cause firms to have less market power (Gaspar and Massa, 2006). Gaspar and Massa (2006) categorized the influence of a firm's position in the competitive market into the following two effects. The first is called the natural hedge effect. According to this effect, severe fluctuations or high instability of firms can be smoothed by a hedge effect based on strong market power. Specifically, when the industries or firms in a region have a stronger market power without heavy competition, they can pass on a bigger portion of the costs from fluctuations to their consumers. On the contrary, industries or firms with low market power in a highly competitive condition might have to lay off employees or close their businesses when they are not able to deal with the fluctuation costs (Gaspar & Massa, 2006; Vuolteenaho, 2002). The second effect is the uncertainty effect. Using this effect, firms with higher market power can minimize the negative impact from instability by reducing information uncertainty. This is because the firms in less competitive conditions are likely to have a more exclusive power to access market information. Additionally, Gaspar and Massa (2006) provided strong empirical evidence that supports these two effects. Therefore, high competition is expected to increase economic instability, whereas low competition is more likely to enhance stability.

The empirical measure for the level of competition in each regional economy is theoretically based on the idea by Porter (1990), who emphasized the role of competition among similar sectors in the process of regional economic growth. Empirically, Glaeser et al. (1992) measured the competition level of industry *n* by the following:

$$competition_n = \frac{f_{ni} / e_{ni}}{F_n / E_n}$$

where f_{ni} is the firm numbers of sector or industry *n* in region *i*; e_{ni} is the employment of sector or industry *n* in region *i*; F_n is the total firm numbers of sector or industry *n* at the national level; E_n is the total employment of sector or industry n at the national level. The above process is similar to calculating location quotients.

Because this competition indicator can only be calculated for each sector or industry, there is a need to develop a modified competition indicator to collectively capture the competition level of the overall economic structure. For this purpose, I generated an overall indicator by summing the competition indicator of each sector, which is weighted by the employment share of each sector. As a result, the overall competition indicator for region i, $COMP_i$ was calculated by:

$$COMP_i = \sum_{n=1}^{N}(S_n \cdot competition_n)$$

where S_n is the (absolute) employment share of sector n and N is the total number of sectors. Like the economic structural indicators, the COMP was also based on the 3-digit level industries of NAICS.

Performance of individual sectors

The economies of many regions can also be determined by the performance of a few specific sectors (Cutler & Hansz, 1971). For instance, the growth of manufacturing sector is still expected to play an important role in the employment growth of MSAs although traditional labor-intensive manufacturing sectors are highly susceptible to global competition (Blumenthal et al., 2009). In terms of economic stability, the performance of individual sectors might significantly affect the regional economic stability. The drastic growth or decline of individual sectors increases the level of economic instability. For instance, in the U.S. metropolitan areas, the high growth based on technology and knowledge-based sectors was more stable than the growth rooted in other industries during the time period from 1980 to 2000 (Chapple & Lester, 2007; Chapple & Lester, 2010).

To select the appropriate sectors to be included in the models, first, I calculated the average annual growth rates for the 10 private super sectors using the aggregated MSAs data based on the QCEW.[23] After that, I identified the sectors that had the highest and lowest growth rate for the overall and four sub-time periods. The annual average growth rates of these selected sectors for each MSA were used as control variables for the performance of individual sectors. Moreover, like economic structural indicators, the growth rates for these sectors for each MSA were also computed by utilizing the CBP data.

[23] Considering all sectors in the 2- or 3- digit level is limited. This is because the 2- or 3- digit level of NAICS are too detail and it is hard to practically select the proper sectors and interpret the effect of these sectors after the analysis. So, to more practically use the NAICS in various empirical analyses, the US Economic Classification Policy Committee (ECPC) suggest the super sectors as alternate industrial classification level by aggregating NAICS sectors into 10 private and 1 public (government) groups.

Table 5.3 Average Annual Growth Rates (%) of Individual Sectors in MSA Overall

Super sectors	Overall period (1998-2010)	Period 1 (1998-2000)	Period 2 (2000-2003)	Period 3 (2003-2007)	Period 4 (2007-2010)
Natural Resources and Mining	-0.05	-1.65	-1.45	2.42	-0.87
Construction	-0.43	4.99	2.94	2.63	-11.48
Manufacturing	-3.35	-0.71	-5.96	-1.65	-4.76
Trade, Transportation, and Utilities	-0.08	2.18	-0.98	1.30	-2.55
Information	-1.01	5.99	-3.17	-2.54	-1.50
Financial Activities	0.44	1.65	2.99	0.54	-3.05
Professional and Business Services	1.39	4.76	0.88	3.15	-2.71
Education and Health Services	2.95	2.02	3.82	3.29	2.23
Leisure and Hospitality	1.71	2.63	1.94	2.37	-0.03
Other services	0.96	1.89	2.95	0.69	-1.29

As presented in Table 5.3, during the overall time period, the manufacturing sector declined the most while the education and health services sector showed the highest growth rates. Specifically, during period 1 (1998-2000) the information sector expanded the most while the natural resources and mining sector declined the most. After period 1, the education and health service sector maintained its position as the fastest growing sector over periods 2, 3, and 4 while the various sectors – the manufacturing sector, the information sector, and the construction sector – were selected as the most declining sector for other periods.

Therefore, for the empirical models based on the overall time period, the manufacturing and the education and health services sectors were selected. Additionally, the natural resources and mining, information, and construction sectors were selected for the panel models using the four sub-time periods.

Educational attainment

Many previous studies pointed out the role of educational attainment in regional economic growth. Theoretically, human capital, which is normally measured by educational attainment, can lead regional economic growth by innovative activities of educated work forces (Lucas, 1988). Chinitz (1962) also recognized the link between city growth and the transmission of skills among skilled or educated people as a propelling factor for economic growth. Additionally, the availability of educated labor might be an important factor in the location decision of firms (Cohen, 2000). Moreover, the cities or communities in which more educated people live are usually regarded as better places to live, providing various amenities. As a result, these places tend to attract more people and firms that can lead to economic growth (Shapiro, 2006). In terms of empirical analyses, there were several empirical studies indicating that the initial level of educational attainment was positively and significantly related to the growth of various economic factors such as income, employment, and population growth (Glaeser & Saiz, 2004; Glaeser, Scheinkman, & Shleifer, 1995; Gottlieb & Fogarty, 2003; Shuai, 2013).

For the relationship between human capital and economic stability, the level of human capital can significantly affect regional economic stability through job composition. This is because the jobs requiring a more educated or skilled labor force are less likely to be affected by layoffs. Furthermore, highly educated people are more likely to find and hold their positions in jobs during bad economic situations, and they can more easily move to other areas with better economic conditions (Malizia & Ke, 1993). It was empirically discovered that the levels of educational attainments were positively related to economic stability (Malizia & Ke, 1993; Trendle, 2006). Therefore, in this study, the percentage of population 25 years or older with at least a bachelor's degree in the MSAs was used as a control variable for educational attainment.[24]

Population size

According to Blumenthal et al. (2009), the population size of a region can affect economic growth in two ways. First, a large economy serving a large population naturally demands a large number of workers. So, the large population might contribute to the increase in employment of regions. Second, the various types of cost savings from agglomeration of economies based on large population size, e.g., reduced transaction and transportation costs (Dixit & Stiglitz, 1977; Krugman, 1993) or reduced searching costs

[24] Considering the time periods of the research, the dataset for educational attainment in 1998, 2000, 2003, and 2007 should be used. I can use the 2000 census data for the educational attainment of the MSA level in 2000. However, there is no possible and appropriate educational attainment data for the MSA level in 1998, 2003, and 2007. For 1998, I used the same variable from the 2000 census data. However, for 2003 and 2007, although the American Community Survey (ACS) data is available from 2006, the 1-year estimates data from ACS has missing observations for some MSAs in these years. So, I used the 3-year (2005-2007) estimates data from the ACS for the 2003 educational attainment in the MSAs and also utilized the 3-year (2007-209) estimates data from the ACS for 2007 educational attainment in the MSAs.

for specialized labor (Quigley, 1998), can also attract more firms or industries into a region. As a result, a region with a large population size can grow more than a region with a small population. Empirical studies have shown that the increase of population size in metropolitan areas was associated with economic growth such as the increase in productivity or average wages (Beeson, 1992; Glaeser & Shapiro, 2001).

On the other hand, population size is also an important control factor for investigating the relationship between economic structure and the level of economic instability. First, with the same amount of employment increase, this increase might mean a drastic change for a small economy with a small population while this increase would only be a minor change for a large economy with a large population. Second, it is suggested by the theory that a region with large population is more likely to have a diversified economic structure (Dissart, 2003; Malizia & Ke, 1993). In other words, a region with a large population size is expected to have the effect of diversity on its economic performance. So, the population size is hypothesized to negatively affect instability. In this study, to empirically control for the effect of population size on both growth and instability, I used the natural log of population size at the initial time point as an explanatory variable. The data for the population size of MSAs was obtained from the Regional Economic Information System (REIS) of the BEA.

Lagged economic performance

According to Glaeser (1994), "the best predictor of whether a region will grow over the next 20 years is whether or not it has grown over the past 20 years"(Glaeser, 1994, p. 19). In other words, the region with a high growth rate in the past is likely to grow more than the region with a low past growth rate. Blanchard, Katz, Hall, and Eichengreen (1992) found a strong correlation between the growth in the early postwar period and the growth in the later postwar period in the U.S. states. Similarly, Glaeser et al. (1995) also observed the persistence of growth rates in the MSAs. On the other hand, although there were several studies that estimated the effect of previous economic growth on present or future economic growth in various regional levels, no one has attempted to investigate the persistence of economic instability, which is another important factor of economic performance in regions. So, as an extension of the persistence of economic performance, I used past instability as the predictor for present or future instability.

Furthermore, previous growth and instability might have cross-effects on growth and instability in the future. More specifically, a high past instability level might have a negative effect on growth in the present or future. Previous studies on the national economy have shown that severe past fluctuations in a nation can constrain present or future investment in that nation, resulting in a slow growth (Caprio, 1997; Stiglitz, 2000). In this study, I want to check whether this correlation holds at the regional level. That is whether the high level of economic instability in a region hinders growth in that region. Moreover, a region with a high growth rate in the past is more likely to attract investment to that region, which allows that region to maintain its economic growth trend in the long-run. This can let the region have a quiet stable economy. In sum, the past growth and instability might be significant predictors for present and future growth and instability. Hence, the average of annual growth rates and instability indicator for the past five years were used as control variables in both growth and instability models. Especially, for the instability indicator, as in the case of dependent variable, the logged value was used.

Regional dummy variables

By using a four-region classification by the U.S. Census Bureau, this study included three regional dummy variables in the models to control for the effects of the geographical locations of the MSAs. This is because the indigenous geographical factors such as climate or historical background, which are shared by the MSAs located in the same geographical regions, might affect economic performance. Specifically, the climate was indicated as one important factor for economic growth because nice weather can attract people and form effective working conditions for employees (Carlino & Mills, 1987). In addition, regional dummy variables can offer an econometric advantage by controlling for potential spatial heterogeneity or spatial autocorrelation, which may not be captured by specific indicators. Moreover, including regional dummy variables also can control for other omitted factors that might vary by regions. So, there is a great deal of empirical studies using regional dummy variables as control factors when estimating economic performance (Blumenthal, Wolman, & Hill, 2009; Drucker, 2011; Glaeser et al., 1992; Malizia & Ke, 1993; Mizuno et al., 2006; Shuai, 2013).

Macroeconomic condition dummy variable

As mentioned in Section 5.1, to see if the relationship between economic structure and performance holds for different macro-economic situations, I applied a panel model approach for the pooled data based on the four sub-time periods. Because these four sub-time periods were based on the macro-economic situations, they consisted of two boom periods – period 1 (1998-2000) and period 3 (2003-2007) – and two bust periods – period 2 (2000-2003) and period 4 (2007-2010). To control for the effect of the characteristics of macro-economic situations, I included a dummy variable to indicate economic boom periods in all the panel models of this study.

Furthermore, in order to more specifically investigate how the effect of each structural indicator is changed by macroeconomic situations, I also included the interaction terms between structural (*DIV* & *MSI*) or structure related variables (*COMP*) and macroeconomic condition dummy variable (*BOOM*). Thus, the panel models had totally three interaction terms (*DIV**BOOM*, *MSI**BOOM*, and *COMP**BOOM*) among their independent variables.

Table 5.4 Descriptions and Sources of Variables

Category	Symbol	Description	Data Source
Dependent Variables	*EG*	Average annual employment growth rates (%)	BLS
	INSTAB	Logged of average deviation between actual employment and predicted employment from a time trends regression and divided by this predicted employment	BLS
Independent Variables	*DIV*	Measuring the diversity of economic structure using the entropy index	CBP
	MSI	The proportion of sectors in an economy with an LQ value larger than one	CBP
Control Variables	*COMP*	Weighted average of competition indicators of 3-digit industries	CBP
	EDUC	Percentage of population 25 years or older with at least a bachelor's degree	Census
	POP	Population size at the initial time points	BLS
	MANU	Average annual growth rate of Manufacturing sector	CBP
	EDH	Average annual growth rate of Education and Health Service sector	
	CONS	Average annual growth rate of Construction sector	
	NRM	Average annual growth rate of Natural Resources and Mining sector	
	INFO	Average annual growth rate of Information sector	
	MW, NE, S	3 Dummy variables for Census regions	Census
	Pre_EG	Average of annual employment growth rates (%) during the last 5 years	BLS
	Pre_INSTAB	Level of instability indicator for monthly employment during the last 5 years	
	BOOM	Macroeconomic condition dummy variable – the economic boom periods have a value of 1.	BLS

(Note: CBP stands for County Business Pattern; BLS stands for Bureau of Labor Statistics)

5.3 Model Specifications

5.3.1 Basic Models

There are two basic models for this analysis. The dependent variable of the first model is the average of annual economic growth rates (*EG*), 1998-2010; and that of the second model is the instability indicator (*INSTAB*), 1998-2010. Regional economic structure was captured by two economic structure indicators – the entropy index for diversity (*DIV*) and multiple specializations indicators (*MSI*). To control for the effects from individual sectors, the average annual growth rates of manufacturing (*MANU*), and education and health services (*EDH*) sectors during the overall time period from 1998 to 2010 were included for both models. In addition, competition indicator (*COMP*), previous growth (*pre_EG*) and previous instability (*pre_INSTAB*) during the last five years (from 1993 to 1998), and three regional dummy variables (*MW, NE, S*) were also included as other control variables. The two basic models, one for growth and the other for instability, were specified as follows:

(1.1) Growth model

$$\begin{aligned} EG = {} & \beta_0 + \beta_1 DIV + \beta_2 MSI + \beta_3 COMP \\ & + \beta_4 MANU + \beta_5 EDH + \beta_6 EDUC + \beta_7 \ln(POP) \\ & + \beta_8 pre\_EG + \beta_9 \ln(pre\_INSTAB) + \beta_{10} MW + \beta_{11} NE + \beta_{12} S + \varepsilon \end{aligned}$$

(1.2) Instability model

$$\begin{aligned} \ln(INSTAB) = {} & \beta_0 + \beta_1 DIV + \beta_2 MSI + \beta_3 COMP \\ & + \beta_4 MANU + \beta_5 EDH + \beta_6 EDUC + \beta_7 \ln(POP) \\ & + \beta_8 pre\_EG + \beta_9 \ln(pre\_INSTAB) + \beta_{10} MW + \beta_{11} NE + \beta_{12} S + \varepsilon \end{aligned}$$

5.3.2 Panel Models

As discussed in Section 5.1, to examine whether the relationships hold during the economic boom and bust periods, I applied a panel analysis for pooled data based on the four sub-time periods. Similar to the basic models, I specified two panel models: one to model economic growth and the other to model stability. The explanatory variables for both models are substantially similar to the basic models in 5.3.1. However, because each cross-sectional data is based on short time periods (e.g., 2 to 3 years), the variables of previous economic performances were excluded from the panel models. Instead, to control for the effects of the performance of individual sectors during all sub-time periods, I included the average annual growth rates of all the sectors that had extreme (either the highest or the lowest) growth rates in the sub-time periods. So, for both panel models, the average annual growth rates of the natural resources and mining (*NRM*), information (*INFO*), manufacturing (*MANU*), education and health services (*EDH*), and construction (*CONS*) sectors were selected. In addition, to control for the effects of an economic boom, the dummy variable for economic boom periods (*BOOM*) and three interaction terms – *DIV*BOOM, MSI*BOOM*, and *COMP*BOOM* – were included in the models. Therefore, the panel models were specified as follows:

(2.1) Growth panel model

$$
\begin{aligned}
EG_{it} = {} & \beta_0 + \beta_1 DIV_{it} + \beta_2 MSI_{it} + \beta_3 COMP_{it} + \beta_4 NRM_{it} \\
& + \beta_5 INFO_{it} + \beta_6 MANU_{it} + \beta_7 EDH_{it} \\
& + \beta_8 CONS_{it} + \beta_9 EDUC_{it} + \beta_{10} \ln(POP)_{it} \\
& + \beta_{11} MW_{it} + \beta_{12} NE_{it} + \beta_{13} S_{it} + \beta_{14} BOOM_{it} \\
& + \beta_{15}(DIV * BOOM) + \beta_{16}(MSI * BOOM) + \beta_{17}(COMP * BOOM) + \varepsilon_{it}
\end{aligned}
$$

(2.2) Instability panel model

$$\begin{aligned}\ln(INSTAB)_{it} = {} & \beta_0 + \beta_1 DIV_{it} + \beta_2 MSI_{it} + \beta_3 COMP_{it} + \beta_4 NRM_{it} \\ & + \beta_5 INFO_{it} + \beta_6 MANU_{it} + \beta_7 EDH_{it} \\ & + \beta_8 CONS_{it} + \beta_9 EDUC_{it} + \beta_{10} \ln(POP)_{it} \\ & + \beta_{11} MW_{it} + \beta_{12} NE_{it} + \beta_{13} S_{it} + \beta_{14} BOOM_{it} \\ & + \beta_{15}(DIV * BOOM) + \beta_{16}(MSI * BOOM) + \beta_{17}(COMP * BOOM) + \varepsilon_{it}\end{aligned}$$

Where: i=MSA; t=time periods (1to 4)

5.4 Estimation Methods

5.4.1 Estimation of the Basic Models

I estimated the two basic models (1.1 and 1.2) by the Ordinary Least Square (OLS) method. The OLS is the most useful and widely used method to estimate the effects of certain factors on other dependent factors (Greene, 2003). Furthermore, the OLS has the greatest virtue in that we can explicitly control for other factors which might affect the dependent variable at the same time (Wooldridge, 2009).

However, simply applying the OLS can be problematic for statistical models incorporating spatial effects. More specifically, in this study, the economic performance of a MSA can be determined not only by the specified explanatory variables in the above models but also by the economic performance of nearby MSAs. The latter process, due to the spatial effects from nearby MSAs, can be assumed to have the issue of spatial autocorrelation. In the case of spatial autocorrelation, theoretically, the estimation results by OLS still have the property of unbiasedness, but it is inconsistent (Elhorst, 2003).

This is because the issue of spatial autocorrelation makes the spatial data violate two important assumptions – uncorrelated error terms and homoscedastic error terms – in the OLS estimation (Can, 1990).

In order to overcome the above problems, spatial econometric analysis, which uses a maximum likelihood estimation method, was suggested by Anselin (1988). A spatial econometric analysis can be done by the following three steps. The first step is to detect spatial effects in the residuals from the OLS estimation by using Moran's I test.[25] If there are no spatial effects in the residuals, there is no need to use a spatial econometric model. The second step is, in the case of verifying spatial effects in the residuals, to select an appropriate type of spatial econometric model[26] by employing the Lagrange Multiplier (LM) test.[27] Finally, the third step is to estimate the parameters in the selected spatial econometric models by using a maximum likelihood technique. Therefore, in this study, I followed the above steps to find the most appropriate models.

5.4.2 Estimation of the Panel Models

There are two estimation methods – fixed effect and random effect estimation – for panel models. In the fixed effect (FE) model, the unobservable effects in the observational unit, which are constant over time, are eliminated by a time-demeaning process (Wooldridge, 2009). Thus, using the FE model has the advantage of controlling

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[25] See Appendix B for a detailed explanation about Moran's I test.
[26] See Appendix C for a detailed explanation about the spatial econometric models and their estimations.
[27] See Appendix D for a detailed explanation about the process of appropriate spatial econometric models by the Lagrange Multiplier (LM) test.

for the unobservable explanatory variables that are constant over time. However, this advantage can be a disadvantage as well. This is because, if the key explanatory variables in the study do not vary much over time, the FE model can lead to imprecise estimates due to the time-demeaning process (Guerra & Cervero, 2011; Wooldridge, 2002). In this study, the main explanatory variables such as diversity (*DIV*) or multiple specializations indicator (*MSI*) do not vary much between the sub-time periods, which will be more specifically discussed in the next chapter. Therefore, the two panel models (2.1 and 2.2) were analyzed using the RE method. The advantage of using the RE model over the FE model is that the RE model allows us to estimate the explanatory variables that are constant over time. This is because the RE model assumes that the unobservable effect, which is constant over time, is uncorrelated with all explanatory variables. Instead, this unobservable fixed effect is regarded as one part of the error term in the panel model. So, this unobservable fixed effect causes a positive serial correlation in the error terms, which might make the estimators inefficient. Hence, the RE model is estimated by using Generalized Least Square (GLS) to deal with this serial correlation (Wooldridge, 2009).[28]

However, according to Wooldridge (2009), there is one important caution in employing the RE model. Comparing the RE model with the FE model, the FE model allows arbitrary correlation between the unobservable effect and all explanatory variables while the RE has an assumption of no correlation between them. So, it is true that the FE is more widely accepted as a better method to estimate ceteris paribus effects

[28] See Appendix E for a detailed estimation process using the GLS in the RE method.

because the time-demeaning process deletes all possible unobservable effects. However, like this study, if the use of the RE model is forced, the model should attempt to include as many time-invariant control variables as possible among the independent variables to control for the time constant fixed effects and to more precisely estimate the effect of key variables (Wooldridge, 2002, 2009). For this purpose, the panel models in this study also included three geographical dummy variables to control for the region-specific fixed effects.

Moreover, similar to the overall models, the panel models can also face the problems of spatial autocorrelation. In order to address the spatial effects in the panel models, I also estimated the parameters in the two panel models by using the spatial random effects method. More specifically, when applying the spatial random effects method, unlike the case of cross-sectional model, there is no suitable specification test for selecting the appropriate spatial effects operator (e.g., spatial lag and error) in the random effects model. So I followed the results of the LM specification test for the cross-sectional models (1.1 and 1.2). Specifically, based on the results of the LM test, the spatial lag model was selected for estimating all the cross-sectional models for the overall time period. Hence, I estimated the two panel models by the spatial lag random effects model, following the process developed by Baltagi, Song, and Koh (2007).[29]

[29] See Appendix F for a detailed explanation about estimating the spatial random effect models.

CHAPTER VI

EMPIRICAL ANALYSIS

As mentioned in Chapter 5, this study mainly consists of both cross-sectional and panel approaches. Cross-sectional models are used to examine the effects of economic structure on regional economic performances from 1998 to 2010, the overall time period of this study. In contrast, panel models are employed to investigate whether the relationships between economic structure and performance hold in different macro-economic situations. Chapter 6 is organized as follows: Section 6.1 focuses on the cross-sectional analysis. I present the basic descriptive statistics and correlation results of the variables used in the cross-sectional regression analyses and then discuss results from the regression analyses. Section 6.2 exhibits and discusses the results from the panel data analyses, taking into account periods of economic boom and bust.

6.1 Cross-sectional Approach for the Overall Time Period

6.1.1 Descriptive Statistics

Table 6.1 shows basic descriptive statistics for all the variables used in the regression analysis. From 1998 to 2010, on average, the employment in the MSA grew about 0.38 percent per year. The average of the instability indicators for the same time period was 0.027. Comparing the coefficients of variation of these two performance variables, the employment growth rate was much more varied in the MSAs than was the instability. For the indicators of past economic performance, on average, employment in the MSAs grew 2.5 percent per year in the five years before 1998. And the average instability in the MSAs five years prior to 1998 was 0.011, which was lower than the instability in this study period.

Table 6.1 Descriptive Statistics for Variables in the Overall Model

Category	Variables	Descriptive Statistics				
		Mean	S.D.	C.V.	Min	Max
Dependent Variables (Economic performance)	*EG* (average of annual growth rates (%) of employment)	0.382	0.965	2.524	-2.325	3.658
	Instability indicator	0.027	0.013	0.475	0.009	0.092
	INSTAB (log of instability indicator)	-3.713	0.409	-0.110	-4.696	-2.388
Economic structural indicators	*DIV* (Entropy index)	3.660	0.127	0.346	2.815	3.877
	MSI (Multiple specializations indicator)	0.375	0.063	0.169	0.108	0.532
Growth rate of individual sectors (%)	*MANU* (Manufacturing)	-2.836	2.493	-0.879	-9.434	12.721
	EDH (Education and health services)	2.528	1.300	0.514	-0.661	9.027
Geographical dummy variables	*MW* (Midwest)	0.252	0.435	1.725	0	1
	NE (Northeast)	0.127	0.334	2.620	0	1
	S (South)	0.405	0.492	1.214	0	1
	W (West)	0.215	0.412	1.912	0	1
Past 5-year economic performance	*Pre_EG*	2.522	1.258	0.499	-0.105	9.423
	Pre_INSTAB	0.011	0.007	0.623	0.002	0.055
	Pre_INSTAB (logged)	-4.652	0.502	-0.108	-6.121	-2.894
Other control variables	*COMP* (Competition indicator)	1.040	0.196	0.189	0.691	2.395
	EDUC (Educational attainment (%))	22.485	7.312	0.325	10.300	52.400
	POP (log of population size)	12.564	1.059	0.084	10.750	16.706

(The number of observations for all variables is 353; S.D. denotes standard deviation; C.V. denotes coefficient of variation)

For economic structural variables, the mean of the *DIV* is 3.66 with a minimum value of 2.815 and a maximum of 3.877. The multiple specializations indicators, *MSI*, show an average of 0.375, indicating that, on average, about 37.5 percent of the three-digit level industries in the MSAs are relatively specialized compared to the national level at the initial time point, 1998. Additionally, the means of growth rates of two individual sectors – manufacturing, and education and health services – were estimated at -2.84 and 2.53 percent, respectively in 1998.

Among other control variables, the competition indicator, which measures the overall level of competition in an MSA, indicates an average of 1.04. At the initial point (1998) of this study period, the average ratio of population 25 years or older with at least a bachelor's degree was estimated at 22.5 percent and the mean of log population size was estimated at 12.6. In addition, for the geographical dummy variables, Table 6.1 indicates that approximately 40 percent of MSAs are in the South region, 12.7 percent are in the Northeast region, 25.2 percent are in the Midwest region and the remaining 21.5 percent are located in the western region. The dummy variable for the MSAs in the western region is omitted in the regression analyses.

6.1.2 Correlation Analysis

Table 6.2 displays the results of the correlation analysis among all the variables used in the overall model. First, the positive and significant correlation between *EG* and *INSTAB* reflects the fact that economic growth always accompanies some economic variation. More specifically, when there is a drastic employment increase, the employment level of that region should experience a large variation caused by this drastic increase in employment, which can be observed as some type of economic instability. However, the small value of the correlation coefficient (0.23) shows that both *EG* and *INSTAB* still measure the different outcomes of regional economic performance. Similarly, two variables of past economic performance are also positively correlated but the correlation coefficient (0.09) is quite small.

Second, the two economic structural variables – *DIV* and *MSI* – are moderately and positively correlated with each other. As pointed out by Dissart (2003) and Malizia and Ke (1993), this positive correlation reflects the fact that the economic structure composed of specialized sectors with similar employment size can be observed as a highly diversified economic structure.

Third, the growth rates of two individual sectors – manufacturing, and education and health services sectors – are positively correlated with each other. This indicates that, despite the different characteristics and performances, the growth rates of these sectors moved in the same direction during this research period from 1998 to 2010.

Fourth, with regard to geographical dummy variables, Table 6.2 shows that the MSAs in the Midwest region show lower levels of employment growth and instability with less multiply specialized structures. The MSAs in the Northeast region only indicate significantly lower levels of instability with more diversified structure. The South MSAs grew relatively faster. Additionally, the West MSAs indicated higher level of both growth and instability.

Table 6.2 Correlation among Variables in Overall Models

	EG	*INSTAB*	*DIV*	*MSI*	*MANU*	*EDH*	*MW*	*NE*	*S*	*W*	*Past EG*	*Past INSTAB*	*COMP*	*EDUC*	*POP*
EG	1														
INSTAB (logged)	0.23**	1													
DIV	-0.09*	-0.25**	1												
MSI	0.28**	-0.11**	0.44**	1											
MANU	0.48**	0.07	-0.03	0.20**	1										
EDH	0.51**	0.36**	-0.08	-0.00	0.19**	1									
MW	-0.38**	-0.18**	0.01	-0.21**	-0.07	-0.23**	1								
NE	-0.08	-0.28**	0.11**	-0.05	-0.13**	-0.16**	-0.22**	1							
S	0.12**	0.05	-0.04	0.08	-0.08	0.04	-0.48**	-0.32**	1						
W	0.32**	0.35**	-0.05	0.16**	0.29**	0.32**	-0.30**	-0.20**	-0.43**	1					
Past EG	0.49**	0.45**	-0.10*	0.02	0.12**	0.46**	-0.15**	-0.35**	0.11**	0.31**	1				
Past INSTAB	0.11**	0.29**	- 0.37**	-0.09*	0.21**	0.09*	-0.01	-0.26**	-0.01	0.22**	0.08	1			
COMP	0.37**	0.26**	-0.10*	0.36**	0.29**	0.19**	-0.31**	0.02	-0.13**	0.46**	0.10*	0.29**	1		
EDUC	0.17**	-0.08	0.00	-0.07	-0.05	0.09*	0.05	0.11**	-0.21**	0.11**	0.17**	-0.24**	-0.08	1	
POP (logged)	-0.04	0.01	0.33**	-0.02	-0.13**	0.07	-0.07	0.12**	-0.02	-0.00	0.06	-0.44**	-0.37**	0.33**	1

(Note: * denotes a p-value < 0.10 and ** denotes a p-value <0.05)

Fifth, Table 6.2 illustrates that in the correlation between the structural variables (*DIV* and *MSI*) and the growth rates of individual sectors, only multiple specializations is significantly correlated with the average annual growth rate of the manufacturing sector while diversity has no significant correlation with the growth rates of both sectors. Last, overall, most of the explanatory variables are significantly correlated with both dependent variables. Furthermore, in most cases, the directions of the correlation are what one might generally expect.

6.1.3 Regression Analysis

Growth models

As specified earlier (See Section 5.3), the following two types of growth models (Models 1 and 2) were estimated. Model 1 is a base model that includes two economic structural indicators and other control variables except for the growth rates of individual sectors. In other words, this model was estimated without controlling for the performance of individual sectors. Model 2 is the unrestricted model that includes the control variables for the performance of individual sectors. Specifically, Model 2 included two more control variables for the growth rates of the manufacturing and the education and health services sectors to control for the effects of the individual sectors that grew or declined the most during this sample period.

Table 6.3 presents the estimation results of these two models. The p-values indicated in the table are basically reported by two-tailed probabilities, although the p-value based on a one-tailed probability is more appropriate for several variables given the directional relationship of my hypotheses. Moreover, all the p-values in the table are computed based on robust standard errors because of heteroscedasticity. Considering the F-statistics, all models are statistically significant (p-values < 0.00) and the values of the adjusted R-squared of these models are estimated at 0.43 and 0.61, respectively.

Results of growth model 1

Both of the economic structure variables, *DIV* and *MSI*, are significant factors that can explain employment growth rates from 1998 to 2010. Diversity was negatively correlated with the growth rate, which supports the Marshall-Arrow-Romer (MAR) theory as discussed in Section 2.1 that specialization promotes economic growth, although this result is opposite of my hypothesis. As expected, the *MSI* was positively associated with the growth rates. The MSAs with a higher proportion of specialized sectors grew faster during the study period.

Model 1 also indicated that the higher the level of competition, the higher the employment growth rate. This effect of competition was statistically significant at a 0.05 level. Education attainment also exerted a positive influence on the employment growth rates. Specifically, a one percentage point increase in population 25 years or older with at least a bachelor's degree was related to a 0.02 percentage point increase of the employment growth rate. The population size variable was found to be insignificant in explaining employment growth.

Table 6.3 Regression Results for the Growth Model, 1998-2010

Variable	Model 1			Model 2		
	Coef	Beta	p-value	Coef	Beta	p-value
Intercept	1.087		0.496	1.136		0.381
Economic structure variable						
Diversity (*DIV*)	-0.990	-0.130	0.024	-0.930	-0.122	0.015
Multiple Specializations (*MSI*)	3.812	0.250	0.000	3.313	0.217	0.000
General control variable						
Competition (*COMP*)	0.778	0.158	0.014	0.426	0.086	0.086
Education (*EDUC*)	0.021	0.157	0.004	0.021	0.161	0.000
Log Population Size (*POP*)	-0.001	-0.001	0.981	-0.023	-0.025	0.585
Geographical dummies						
Midwest region (*MW*)	-0.451	-0.203	0.007	-0.218	-0.098	0.113
Northeast region (*NE*)	0.101	0.035	0.552	0.362	0.125	0.008
South region (*S*)	0.031	0.016	0.813	0.233	0.118	0.041
Performance of Individual sectors						
Manufacturing (*MANU*)				0.135	0.349	0.000
Education and health services (*EDH*)				0.200	0.269	0.000
Past performance						
Past_5year_growth (*Past_EG*)	0.310	0.405	0.000	0.222	0.290	0.000
Past_5year_instability (*Past_INSTAB*)	0.100	0.052	0.387	-0.002	-0.001	0.977
R-squared	0.447			0.621		
Adjusted R-squared	0.430			0.608		
Number of Observations	353					

The only significant geographical dummy variable is the one for Midwest. Compared to the West, which was the omitted geographical dummy variable, the employment in the Midwest MSAs grew about 0.5 percentage points less per year during this study period from 1998 to 2010. The geographical dummy variables for the Northeast and South regions were insignificant in Model 1. Moreover, the employment growth in MSAs showed path dependency over time. The MSAs had grown faster in the five years before the study period and continued to grow faster during the period from 1998 to 2010. In contrast, past instability did not significantly affect the employment growth during the same period.

To understand the relative importance of the explanatory variables, I looked at the beta-coefficients. I found that, among two structural variables, the *MSI* was relatively more important in determining employment growth. With regard to other variables, the variable for the employment growth was revealed as the strongest predictor for employment growth rates in this study period.

Results of growth model 2

The estimated results for both structural indicators are almost the same as the results in Model 1. The *DIV* consistently showed the negative coefficient. Also, the *MSI* consistently indicated a positive and significant influence although the magnitude of this coefficient dropped slightly. The effects of both indicators were highly statistically significant at a 0.05 level.

Among the general control variables, even if the statistical significance of the competition weakened in Model 2, the positive effect of the *COMP* was still significant at a 0.10 level (with a one-tailed probability, still significant at a 0.05 level). The education attainment consistently showed a positive effect with the same amount of coefficient. However, like Model 1, the initial population size had no significant association with the employment growth rate.

Unlike the case of Model 1, the dummy variables for both the Northeast and South regions showed positive and significant effects in Model 2. The spatially heterogeneous growth pattern of individual sectors might interact with the effects from the geographical dummy variables and hence might affect the estimation results for these dummy variables. The results of Model 2 indicated that, compared to the West, the employment in the Northeast and South MSAs grew respectively about 0.36 and 0.23 percentage points more per year. In addition, the growth rates of both the manufacturing and education and health services sectors had a positive and significant influence on the growth rate in Model 2. A one percentage point increase in both sectors will increase the employment growth rates by a 0.135 percentage point and a 0.200 percentage point, respectively. With the past economic performance, only the effect of the past economic growth was statistically significant in Model 2.

For the beta-coefficients, while the magnitudes of the beta-coefficients for two structural variables slightly decreased, the growth rate of the manufacturing sector showed the largest value, which means that the growth rate of the manufacturing sector might be relatively the most influential determinant of economic growth in MSAs.

Results of the spatial econometric growth model

As mentioned in Section 5.4, growth models are also estimated by the appropriate spatial econometric model. Before applying the spatial econometric model, using the Moran's *I* test, I detected a spatial autocorrelation in the residuals from the OLS estimation. The results from the Moran's *I* test indicated that each residual from both models is significantly spatially auto-correlated. I then applied the Lagrange Multiplier specification test to select a more appropriate type of spatial econometric model for each case. The LM test statistics showed that the spatial lag model is a better option for these two models.[30] Table 6.4 presents the estimation results of the spatial econometric growth models. The coefficient for the spatially lagged dependent variable, rho (ρ), was statistically significant in all models, indicating that the employment growth rate in an MSA was positively associated with the employment growth rate in neighboring MSAs. In all spatial models, the MSI indicated a positive and significant effect on the employment growth rate while the DIV showed a negative and significant coefficient. This result is very consistent with the result obtained by the OLS, suggesting that the effects of overall economic structure are significant determinants of economic growth in the MSAs even when controlling for the effects of economic growth in neighboring MSAs.

[30] The detailed results from the Moran's I and the LM tests are shown in Appendix G.

Table 6.4 Spatial Regression Results for the Growth Model, 1998-2010

Variable	Model 1		Model 2	
	Coefficient	p-value	Coefficient	p-value
Intercept	0.663	0.600	0.815	0.443
Economic structure variable				
Diversity (*DIV*)	-0.793	0.032	-0.787	0.011
Multiple Specializations (*MSI*)	3.158	0.000	2.871	0.000
General control variable				
Competition (*COMP*)	0.691	0.007	0.381	0.082
Education (*EDUC*)	0.022	0.000	0.022	0.000
Log Population Size (*POP*)	-0.006	0.885	-0.026	0.486
Geographical dummies				
Midwest region (*MW*)	-0.133	0.363	0.006	0.963
Northeast region (*NE*)	0.279	0.077	0.479	0.000
South region (*S*)	0.158	0.173	0.315	0.001
Share of Individual sectors				
Manufacturing (*MANU*)			0.126	0.000
Education and health service (*EDH*)			0.191	0.000
Construction (*CONS*)				
Past performance				
Past_5year_growth (*Past_EG*)	0.278	0.000	0.202	0.000
Past_5year_instability (*Past_INSTAB*)	0.125	0.161	0.023	0.761
Spatially lagged Economic Growth (ρ)	0.376	0.000	0.280	0.000
Number of Observations	353			

There were some changes in the results for the geographical dummy variables. In Model 1, the Midwest dummy variable, which was significant in the OLS, was not significant by the spatial lag model. Otherwise, the dummy for the Northeast region, which was insignificant in the OLS results, was revealed as a significant factor by the spatial lag estimation. These changes can be explained by the controlling effect for geographical heterogeneity in the spatial lag model because geographical heterogeneity can be observed as some types of spatial autocorrelation. Thus, the controlling effect for geographical heterogeneity by these dummy variables can be interfered with by the spatially lagged dependent variable in the spatial lag model, bringing the change in statistical significances for the geographical dummy variables. Last, except for the geographical dummy variables in Model 1, the spatial lag models yielded substantially similar estimation results with the OLS estimation.

Summary of growth model results

In the base models, the empirical results suggested that the multiple specializations, competition, educational attainment, and past economic growth helped to increase the employment growth rate and the spillovers from neighboring MSAs were influential as well. However, the results showed that the level of diversity was negatively associated with employment growth, which is the opposite of my hypothesis based on Jacobs' theory. Instead, this result supports the theory by the Marshall-Arrow-Romer (MAR) that specialization is an important driving force for regional economic growth.

Additionally, the models with the control variables for the growth rates of individual sectors (unrestricted models) yielded substantially similar results. Among the main explanatory variables, multiple specializations, educational attainment, and past economic growth were still comprehended as the main factors that positively affect the employment growth rate while diversity was estimated to have a negative effect. Overall, the results suggested that economic diversification might no more be an effective tool for regional economic growth. Instead, enhancing the specialization might be a more appropriate option for growth. Furthermore, the results showed that MSI is a consistently and positively significant indicator to predict employment growth.

The variable of educational attainment consistently showed a positive effect in all types of models, indicating the importance of an educated labor force to regional economic growth. Also, the positive effect of competition, which was strongly emphasized by Porter (1998), was also statistically significant in all models. However, the logged population size at the initial time point was consistently estimated to have no significant association with the employment growth rate in MSAs, suggesting that agglomeration economies based on large population size no longer effectively contribute to recent economic growth.

The performance of both manufacturing, and education and health services sectors contributed to the employment growth rate in MSAs during this study period. Because I measured the performance of these sectors using the average annual growth rate of employment, the performance of these sectors and the dependent variable (growth rate of employment in MSAs) should move in the same direction as the overall growth rate and therefore result in a positive association. Comparing the magnitudes of coefficients between two sectors, the effect of a one percentage point increase in the growth rate of the education and health services sector (a 0.191 percentage point) was larger than that of the manufacturing sector (a 0.126 percentage point). However, in terms of relative influential power, among all the explanatory variables, the *MANU* showed the largest value of the beta-coefficient.

The persistence of employment growth was significantly observed in all estimation results, which is quite coherent with the previous findings by Blanchard et al. (1992) and Glaeser et al. (1995). So, the result suggested that the employment growth in MSAs have a path dependent pattern over time, which supports the hypotheis that the MSAs with high employment growth rates in the past are more likely to grow faster currently and in the future.

Instability models

Table 6.5 presents the results of the instability models estimated by the OLS. The p-values were calculated using robust standard error due to heteroscedasticity. The F-statistics of all models are statistically significant (p-values < 0.00) and the values of the adjusted R-squared of these models ranged from 0.38 to 0.39.

Results of instability model 1

In Model 1, both the *DIV* and *MSI* had a negative and significant influence on the employment instability in MSAs during this study period from 1998 to 2010. The result of the *DIV* is strongly consistent with the theoretical and empirical expectations of many previous studies. The economies of the MSAs with a higher level of diversity were more stable during this study period. Moreover, as expected by the hypothesis, the result showed that a high level of multiple specializations might reduce the level of employment instability in regions.

All the general control variables – competition, educational attainment, and population size – significantly affected the employment instability during the study period. The more competitive economies MSAs have, the higher their employment instability. Otherwise, the MSAs with the more educated people experienced less employment instability during the overall time period. Specifically, a one percentage point increase in the *EDUC* was associated with about a one percent decrease in the employment instability indicator. In addition, because the initial population size was used as a logged value in the models, the coefficient *POP* can be interpreted as the elasticity. The estimated elasticity of instability with respect to initial population size was 0.097, which indicates that a one percent increase in the population size increases the employment instability indicator by about 0.1 percent.

All three geographical dummy variables were significantly and negatively associated with employment instability. Specifically, compared to the West region, the MSAs in the Midwest, Northeast, and South experienced more stability in their employment during this study period. In addition, similar to growth, employment instability in MSAs also indicated a path dependent pattern over time. The MSAs that had experienced a higher instability in the five years prior to 1998 continued to show a higher level of instability from 1998 to 2010. Moreover, past employment growth was also positively and significantly associated with the current employment instability. In detail, a one percentage point increase in the path employment growth rate was related to a 10.8 percent increase in instability from 1998 to 2010.

The beta-coefficients of the two structural variables indicated that the *MSI* was slightly more important in determining the level of employment instability. Among other explanatory variables, the past employment growth is relatively the most influential factor that can increase employment instability. Similarly, the variables *COMP* or *POP*, which were positively associated with employment instability, showed relatively more strength in explaining the employment instability.

Table 6.5 Regression Results for the Instability Model, 1998-2010

Variable	Model 1			Model 2		
	Coef	Beta	p-value	Coef	Beta	p-value
Intercept	-2.934		0.000	-2.964		0.000
Economic structure variable						
Diversity (*DIV*)	-0.422	-0.130	0.018	-0.428	-0.132	0.015
Multiple Specializations (*MSI*)	-1.117	-0.173	0.001	-0.967	-0.150	0.005
General control variable						
Competition (*COMP*)	0.525	0.252	0.000	0.516	0.247	0.000
Education (*EDUC*)	-0.010	-0.171	0.001	-0.010	-0.173	0.001
Log Population Size (*POP*)	0.097	0.249	0.000	0.092	0.237	0.000
Geographical dummies						
Midwest region (*MW*)	-0.147	-0.156	0.018	-0.130	-0.139	0.041
Northeast region (*NE*)	-0.251	-0.205	0.000	-0.245	-0.200	0.000
South region (*S*)	-0.094	-0.113	0.097	-0.093	-0.111	0.098
Performance of Individual sectors						
Manufacturing (*MANU*)				-0.013	-0.077	0.129
Education and health service (*EDH*)				0.034	0.108	0.067
Past performance						
Past_5year_growth (*Past_EG*)	0.109	0.335	0.000	0.097	0.299	0.000
Past_5year_instability (*Past_INSTAB*)	0.114	0.140	0.006	0.121	0.149	0.003
R-squared	0.402			0.414		
Adjusted R-squared	0.385			0.393		
Number of Observations	353					

Results of instability model 2

Similar to Model 1, the *DIV* and *MSI* were consistently and significantly related to reducing employment instability. Additionally, the estimation results for the general control variables were also quite similar to Model 1. *COMP* consistently increased the instability. The elasticity between *INSTAB* and *POP* was estimated at 0.08. As *EDUC* increases by 1 percentage point, the instability indicator will decrease by 0.8 percent. Moreover, the estimation results for the geographical dummy variables are also substantially the same as Model 1.

For the effect of individual sectors, only the average annual growth rate of the education and health services sector was significantly associated with employment instability. Because the education and health services sector grew the most during the overall time period, this high growth brought instability to overall employment growth. More specifically, a 1 percentage point increase in the growth rate of the education and health services sector will increase the instability indicator by about 3.4 percent.

Last, considering the beta-coefficients, competition, past economic growth, and population size are comprehended as the relatively more important factors in explaining the employment instability in this study period. However, the growth rates of individual sectors, which indicated the large value of beta-coefficients in the growth model, did not show the distinguished value in the instability model.

Results of the spatial econometric instability model

The instability models were also estimated by the appropriate spatial econometric model. The Moran's *I* test identified the significant level of spatial autocorrelation in each residual from all models, as shown in Table 6.5. The Lagrange Multiplier (LM) test suggested that using the spatial lag model is more appropriate for all models, as illustrated in Table 6.5.[31] Table 6.6 presents the estimation results of spatial lag instability models. The coefficient for the spatially lagged dependent variable, rho (ρ), was statistically significant in all models, suggesting that the level of employment instability in an MSA is significantly affected by the levels of instability in the neighboring MSAs.

In the estimation results, except for the geographical dummy variables and the effect of the manufacturing sector, the signs, and statistical significance of the estimated coefficients shown in Table 6.6 were substantially similar to the results by the OLS estimation presented in Table 6.5 although the magnitude of coefficients are all slightly decreased by the spatial lag estimation.

For the geographical dummy variables, all these variables had no statistically significant effect in the spatial lag model. As explained in the growth model case, the controlling effect for geographical heterogeneity by the dummy variables can be invaded by the effect from the spatially lagged dependent variable in the spatial lag model. As a result, the statistical significance for the geographical dummy variables can be changed by applying the spatial lag model.

[31] The detail results from the Moran's I and the LM test are reported in Appendix G.

Table 6.6 Spatial Regression Results for the Instability Model, 1998-2010

Variable	Model 1		Model 2	
	Coefficient	p-value	Coefficient	p-value
Intercept	-1.458	0.013	-1.474	0.011
Economic structure variable				
Diversity (*DIV*)	-0.273	0.086	-0.278	0.076
Multiple Specializations (*MSI*)	-1.045	0.001	-0.893	0.005
General control variable				
Competition (*COMP*)	0.404	0.000	0.393	0.000
Education (*EDUC*)	-0.008	0.001	-0.008	0.001
Log Population Size (*POP*)	0.063	0.001	0.058	0.002
Geographical dummies				
Midwest region (*MW*)	-0.047	0.435	-0.029	0.635
Northeast region (*NE*)	-0.073	0.317	-0.066	0.369
South region (*S*)	-0.034	0.499	-0.032	0.524
Performance of Individual sectors				
Manufacturing (*MANU*)			-0.013	0.061
Education and health service (*EDH*)			0.035	0.014
Past performance				
Past_5year_growth (*Past_EG*)	0.106	0.000	0.094	0.000
Past_5year_instability (*Past_INSTAB*)	0.095	0.014	0.102	0.008
Spatially lagged Economic Growth (ρ)	0.456	0.000	0.460	0.000
Number of Observations	353			

In addition, the growth rate of the manufacturing sector, which had no significant effect in the OLS results, turned out to be negative and significant in the spatial lag model. Specifically, a 1 percentage point increase in the growth rate of the manufacturing sector might decrease the instability indicator by about 1.3 percent. This result indicates that, unlike the education and health service sector, the fast growth of the manufacturing sector might help to enhance employment stability although this sector declined the most during this research period. A 1 percentage point increase in the growth rate of the education and health services sector would increase the level of instability by about 0.035 percent, which is the almost the same as the OLS result shown in Table 6.5.

Summary of instability model results

Except for the geographical dummy variables, all types of instability models yielded fundamentally similar estimation results. These models showed that high diversity, high multiple specializations, and high educational attainment help regions secure their economic stability. In contrast, more competition, large population size, high past economic growth, and a high growth rate of the education and health services sector were estimated to have decreased employment stability. As expected, both diversity and multiple specializations in overall economic structure have played an important role in reducing employment instability and therefore enhanced economic stability in the MSAs. Moreover, it should be noted that, unlike the growth models, the magnitudes of beta-coefficients for economic structural variables are larger than those of individual sectors. This indicates that, compared to the effects of individual sectors, the effects of overall economic structure are more influential in determining the employment instability in MSAs.

Competition also had a positive and significant influence on the employment instability in all models. This finding supports the argument by Gaspar and Massa (2006) that, in a highly competitive market condition, firms tend to easily layoff their employees to cope with the cutthroat competition, resulting in a high level of employment instability. The notable fact is that the results of growth models consistently showed that competition had a positive effect on economic growth. So, combining the results from both growth and instability models suggests that a competitive economic condition can be a double-edged sword for simultaneously promoting both growth and instability. This is because high competition promotes economic growth while it can also severely increase economic instability at the same time. In other words, both growth and stability will hardly be achieved simultaneously by reinforcing competition.

In addition, the initial population size is consistently and positively associated with employment instability which is the opposite of the theoretical assumption that the MSAs with a large population size are more likely to be stable. The results showed that the MSAs with a large population tend to be more unstable in terms of employment. This opposite result implies that the MSAs with a large population may be growing or declining faster than the smaller ones and therefore increase the instability. Moreover, educational attainment consistently had a positive influence on employment stability in all the results. This result supports the expectation by Malizia and Ke (1993) that highly educated people are hardly affected by layoffs and therefore they are more likely to maintain their occupational positions even during the recessions, resulting in enhancing economic stability.

The fastest growing sector (education and health services) was consistently and positively associated with the employment instability, which shows that the radical growth of specific sectors might increase the instability in MSAs. The declining sector (manufacturing) had a negative coefficient, which was only statistically significant in the results in the spatial lag model. In all models, both employment growth and instability during the five years before 1998 had a positive effect on employment instability from 1998 to 2010.

Between the OLS and spatial lag models, there were some differences in the estimation results for the geographical dummy variables. Specifically, the spatial lag models produced no statistically significant coefficients for the geographical dummy variables. As repeatedly explained, the geographic locational effects explained by these dummy variables may also be accounted for by the spatially lagged dependent variable. Therefore, with the spatial lag variable in the model, the geographical dummy variables lost their significance.

6.2 Panel Approach for Four Sub-Time Periods

6.2.1 Descriptive Statistics

Panel data was constructed for the four sub-time periods based on the macro-economic conditions. The first and third periods are the economic boom periods while the second and fourth present the economic bust periods. Table 6.7 provides the descriptive statistics for the variables that were used in the panel models, by each sub-time period.[32] First, the first row of Table 6.7 shows that the average annual employment growth rates in the MSAs fluctuated with the macro-economic situations during this sample time period. The average employment growth rates (*EG)* for the economic boom periods were 1.95% (Period 1) and 1.56% (Period 3), respectively, much higher than those during the economic bust (-0.070% and -1.672 respectively). The level of employment instability showed a gradually decreasing pattern over all sub-time periods except for a slight increase from period 2 to period 3. In addition, the coefficients of variation for the *EG* were much larger than those for the *INSTAB* in all periods, which indicates, employment growth was relatively far more varied than employment instability in the MSAs.

Second, the basic descriptive statistics for both economic structural indicators were quietly time-invariant given the four sub-time periods. For diversity, the means of the diversity indicator for all periods were consistently estimated at around 3.65 - 3.66. Also the means of the *MSI* were also steadily rated at around similar values (0.370 - 0.375). Furthermore, other statistics related to the dispersion of data also presented quite

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[32] Because of their time-invariant nature, the geographical and macroeconomic condition dummy variables are excluded in Table 6.7.

stable levels although there was a slightly decreased pattern in the standard deviation of the *MSI*. Hence, as mentioned in Chapter 5, the time-constant or invariant nature of the economic structural indicators led us to apply the random effects model for estimating the parameters in these panel models. This is because, if the main explanatory variables are time invariant, employing the fixed effects model might produce counter- or non-intuitive results with an extremely low level of goodness of fit. Thus all panel models in this study were basically estimated as a random effects model.

Table 6.7 Descriptive Statistics of the Panel Data

Variables	Statistics	Period 1	Period 2	Period 3	Period 4
EG (average of annual growth rates (%) of employment)	Mean	1.954	-0.070	1.556	-1.672
	Std. Dev.	1.547	1.625	1.465	1.381
	Coef. Var.	0.792	-23.219	0.941	-0.826
Instability indicator	Mean	0.008	0.009	0.009	0.013
	Std. Dev.	0.008	0.005	0.006	0.006
	Coef. Var.	1.032	0.580	0.737	0.434
INSTAB (log of instability indicator)	Mean	-5.051	-4.868	-4.920	-4.425
	Std. Dev.	0.570	0.451	0.514	0.368
	Coef. Var.	-0.113	-0.093	-0.104	-0.083
DIV (Entropy index)	Mean	3.660	3.655	3.665	3.646
	Std. Dev.	0.127	0.121	0.123	0.116
	Coef. Var.	0.035	0.033	0.034	0.032
MSI (Multiple specializations indicator)	Mean	0.375	0.373	0.370	0.374
	Std. Dev.	0.063	0.060	0.057	0.055
	Coef. Var.	0.169	0.162	0.155	0.147
COMP (Competition indicator)	Mean	1.040	1.046	1.039	1.058
	Std. Dev.	0.196	0.193	0.185	0.178
	Coef. Var.	0.189	0.185	0.178	0.168
EDUC (Educational attainment (%))	Mean	22.485	22.485	24.690	25.206
	Std. Dev.	7.312	7.312	7.862	7.777
	Coef. Var.	0.325	0.325	0.318	0.309
POP (log of population size)	Mean	12.580	12.601	12.629	12.674
	Std. Dev.	1.052	1.056	1.061	1.063
	Coef. Var.	0.084	0.084	0.084	0.084

(Std.Dev. denotes Standard Deviation and Coef.Var. denotes Coefficient of Variation)

Third, with the general control variables, the competition indicator (*COMP*) also fluctuated with the macro-economic situations. Specifically, there was higher competition at the ends of both economic boom periods (that is also the beginnings of the economic bust periods). However, after the economic busts, there was less competition in the economy. Additionally, the level of educational attainment progressively expanded (from 22.49 to 25.21%) during this sample time period. Similarly, the logged value of population size also followed a trend of slight increase during the same time period, regardless of the types of macro-economic situations.

Fourth, as specified in Chapter 5, to control for the effects from the individual sectors, the sectors with the most growth and decline – natural resources and mining (*NRM*), information (*INFO*), manufacturing (*MANU*), education and health services (*EDH*), and construction (*CONS*) – for each sub-time periods were included in the panel models. Accordingly, Table 6.8 presents the descriptive statistics for the average annual growth rates of five selected individual sectors for the sub-time periods.

Regardless of the macro-economic situations, the mean of the average annual growth rate of the manufacturing sector for each period consistently showed a negative value, indicating a declining pattern in the manufacturing sector. An interesting fact is that these negative growth rates fluctuated with macroeconomic situations. So, although they still showed a negative value, the magnitudes of decline during an economic boom were much smaller than those observed during an economic bust. In contrast, the growth rate of the education and health services sector had a positive value for all time periods, which shows that education and health services had grown over all sub-time periods.

Additionally, the natural resources and mining sector showed a gradually increasing pattern in its growth rates during periods 1, 2, and 3 but it drastically declined during period 4.

Table 6.8 Descriptive Statistics of Growth Rates (%) of Selected Sectors

Variables	Statistics	Period 1	Period 2	Period 3	Period 4
NRM (Natural Resources and Mining)	Mean	5.410	6.087	11.554	-0.626
	S. D.	35.023	35.714	42.342	46.307
	C. V.	6.474	5.867	3.665	-73.940
CONS (Construction)	Mean	5.620	-0.912	3.176	-8.318
	S. D.	5.146	4.899	4.512	6.435
	C. V.	0.916	-5.374	1.420	-0.774
MANU (Manufacturing)	Mean	-0.686	-3.571	-0.916	-6.095
	S. D.	4.197	4.932	3.733	4.400
	C. V.	-6.117	-1.381	-4.074	-0.722
INFO (Information)	Mean	4.950	2.629	-0.199	-2.222
	S. D.	8.870	8.766	6.829	7.930
	C. V.	1.792	3.334	-34.267	-3.569
EDH (Education and Health Services)	Mean	2.220	3.705	2.290	1.875
	S. D.	3.579	3.694	2.153	1.775
	C. V.	1.612	0.997	0.940	0.947

Moreover, the average annual growth rate of the construction sector fluctuated with the macro-economic situations. The average employment growth rate of the construction sector showed a positive value for periods 1 (5.6%) and 3 (3.2%) while it had a negative value for periods 2 (-0.9%) and 4 (-8.3). In addition, the growth rate of the information sector was positive before period 3. However, the radical collapse of the IT bubble during period 2 might have pushed the information sector into a declining state. So, since period 3, the information sector had shown a negative growth rate.

6.2.2 Panel Analysis

Growth panel models

The growth panel model, which was specified earlier in Section 5.3, was estimated. To estimate the effects of economic structural indicators, which can be contingent on the performance of individual sectors, I estimated the two types of models: Model 1 is a base model that does not include the control variables for the effects from the performance of individual sectors and Model 2 is an unrestricted model including the control variables for the growth rate of the individual sectors which grew or declined the most over the sub-time periods. Moreover, as showed in Table 6.9, each model was estimated by two methods – the pooled OLS regression and the random effects GLS regression. The p-values indicated on all columns are basically computed based on two-tailed probabilities.

Results of growth panel model 1

The diversity level of the overall economic structure had a negative and significant association with the average of annual employment growth rates. This result supports the theory by Marshall-Arrow-Romer that specialization positively affects economic growth. However, the *MSI* was positively and significantly associated with the employment growth rate, which strongly supports the argument that specializing in multiple industrial pursuits promotes regional economic growth. This finding is consistent for both the OLS and random effects regression models, although the magnitudes of the coefficients of economic structural indicators slightly decreased in the random effects model.

However, the estimation results for the macroeconomic dummy variable (*BOOM*) and the interaction terms indicated that the effects of the overall economic structure might be changed by different macroeconomic situations. As expected, the dummy variable (*BOOM*) that indicated economic boom periods was positive and significant. Additionally, this dummy variable (*BOOM*) and its interaction terms with structural variables (*DIV* and *MSI*) were also jointly significant. More specifically, compared to the economic bust periods, in both estimation cases, the MSAs observed about 2.66[33] percentage points more employment growth rate when other factors were fixed and all three structural variables have their mean values. Moreover, in both estimation methods, the diversity had a negative effect on the employment growth rate while this negative effect might decrease during an economic boom. The interaction term (*DIV**BOOM*) between diversity and the economic boom dummy variable was estimated to have a positive coefficient. So, overall, we might expect a negative effect from diversity on the employment growth rate for the short sub-time periods and we also can expect that the magnitude of this effect would decrease during an economic boom. Similarly, considering the negative effect of the interaction term between *MSI* and *BOOM*, the positive effect of *MSI* is expected to decrease during an economic boom, especially since the magnitude of the coefficient of the interaction term (*MSI**BOOM*) was almost the same as that of the *MSI*. The combined effect of *MSI* during an

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[33] At *DIV*=0 (centered), *MSI*=0.37, and *COMP*=1.04, in the random effect model, the predicted difference between economic boom and bust is 4.017 + (0.37*-5.40) + (1.04*0.63) ≈ 2.66.

economic boom became trivial.[34] Otherwise, the positive effect of *COMP* was only presented during an economic boom because the interaction term between *COMP* and *BOOM* had a positive value with a joint significance with *BOOM* while the main effect of *COMP* was insignificant.

Among the general control variables, both the competition and initial population size have no significant influence on the growth rate in both the pooled and random effects models. However, educational attainment had a significant and positive coefficient in the results from the pooled OLS while it was estimated to have no significant effect from the random effects estimation. The p-value for *EDUC* in the pooled OLS regression was calculated based on the usual OLS standard errors. However, in the panel data structure, this usual OLS standard error tended to underestimate the true standard error because the OLS regression generally ignores the positive serial correlation which is quite frequently observed in a panel model (Wooldridge, 2009). So, to rectify the underestimated standard error, the random effects model used the generalized least square (GLS) to estimate the parameters. Hence, the difference of estimation procedures for dealing with serial correlation in the error term can produce a difference in the statistical significance of *EDUC* between the pooled OLS and the random effects models.

[34] In both estimation results, the result of a post-estimation parameter test did not reject the null hypothesis that the combined effects of MSI and MSI*BOOM is zero with a p-value of around 0.77 - 0.78.

Table 6.9 Regression Results for the Growth Panel Model

Variable	Model 1				Model 2			
	Pooled OLS		Random effects		Pooled OLS		Random effects	
	Coef	p-value	Coef	p-value	Coef	p-value	Ceof	p-value
Intercept	-4.052	0.000	-3.705	0.001	-3.199	0.000	-3.021	0.000
Macroeconomic condition dummy								
Economic boom periods (*BOOM*)	3.871	0.000	4.017	0.000	2.554	0.000	2.610	0.000
Economic structure variable								
Diversity (*DIV*)[35]	-2.455	0.000	-2.326	0.000	-2.224	0.000	-2.133	0.000
Multiple Specializations (*MSI*)	5.406	0.000	5.043	0.000	4.071	0.000	3.889	0.000
Interaction terms: Economic structure variable*BOOM / Competition*BOOM								
*DIV*BOOM*	1.694	0.037	1.723	0.024	1.725	0.004	1.729	0.002
*MSI*BOOM*	-5.052	0.004	-5.399	0.001	-4.019	0.002	-4.160	0.001
*COMP*BOOM*	0.645	0.188	0.625	0.175	0.065	0.855	0.063	0.854
General control variable								
Competition (*COMP*)	0.467	0.234	0.518	0.232	0.578	0.044	0.578	0.056
Education (*EDUC*)	0.017	0.005	0.006	0.393	0.025	0.000	0.024	0.000
Log Population Size (*POP*)	0.045	0.360	0.046	0.451	0.048	0.185	0.044	0.283
Geographical dummies								
Midwest region (*MW*)	-0.743	0.000	-0.760	0.000	-0.426	0.000	-0.448	0.000
Northeast region (*NE*)	-0.492	0.001	-0.485	0.009	-0.274	0.015	-0.291	0.020
South region (*S*)	-0.158	0.201	-0.192	0.207	0.028	0.758	0.016	0.874
Performance of Individual sectors								
Natural Resources and Mining (*NRM*)					-0.001	0.488	0.000	0.507
Construction (*CONS*)					0.124	0.000	0.124	0.000
Manufacturing (*MANU*)					0.098	0.000	0.097	0.000
Information (*INFO*)					0.027	0.000	0.026	0.000
Education and Health Services (*EDH*)					0.058	0.000	0.051	0.000
Overall R-squared	0.4519		0.4503		0.7090		0.7088	
Number of Observations	1412							

[35] To avoid the extremely high correlation between the interaction term (*DIV*BOOM*) and the economic boom dummy variable, I centered *DIV* about its mean before creating the interaction variable.

Midwest and Northeast dummy variables were both significant. Compared to the West region (base group), the MSAs in the Midwest region observed a 0.74 - 0.76 percentage point lower employment growth rates and the MSAs in the Northeast region showed an approximately 0.49 percentage point lower growth rate.

Last, except for educational attainment, there was no significant difference in the estimation results between the OLS and the random effects regression. Although the magnitudes of the coefficients of economic structural indicators slightly decreased in the random effects model, the directions and statistical significance of coefficients were still the same in both estimation results.

Results of growth panel model 2

Both diversity and multiple specializations indicators had almost the same estimation results although the magnitudes of the effects were slightly smaller in Model 2. So, diversity still negatively affected the employment growth rate while multiple specializations consistently and positively affected the growth rate over the sub-time periods.

In addition, similar to Model 1, the economic boom dummy variable (*BOOM*) had a positive and significant influence. The estimation results for the interaction terms were also quite similar to those of Model 1. Specifically, compared to the economic bust periods, in both estimation methods, the MSAs grew about 1.12 ~1.13 percentage points more per year during economic boom periods when other control variables were fixed and three structural variables had their mean values. Moreover, during economic boom periods, the negative effect of diversity decreased and the effect of multiple specializations also collapsed to the amount of about zero.[36] However, the effect of competition slightly increased during boom periods.

With the general control variables, the association between the initial population size and the employment growth rate was still insignificant. However, competition, which was estimated as an insignificant factor in Model 1, showed a significant and positive effect in Model 2. This result evidenced the argument by Porter (1998) that competition can spur innovative activities in regions and therefore bring economic prosperity. Similarly, the effect of educational attainment, which was only significant in the OLS in Model 1, became strongly significant in both the OLS and panel models. In detail, a 1 percentage point increase in *EDUC* is associated with about a 0.024 - 0.025 percentage point increase in the employment growth rate.

The estimation results for the geographical dummy variables were substantially similar to Model 1. Compared to the MSAs in the West region, those in the Midwest region observed about a 0.43 - 0.45 percentage point lower employment growth rate and those in the Northeast region showed approximately a 0.27- 0.29 percentage point lower growth rate.

Among the performance of individual sectors, except for the natural resources and mining sector, the average annual growth rates of all other sectors were positively and significantly associated with the employment growth rate over the sub-time periods.

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[36] In both estimation results, the result of a post-estimation parameter test did not reject the null hypothesis that the combined effects of *MSI* and *MSI**BOOM* is zero with high p-values (0.95 for the pooled model and 0.77 for the random effects model).

With a 1 percentage point increase in the growth rate of each sector, the construction sector is expected to increase the employment growth rate for MSAs by about a 0.12 percentage point, which is the largest value among the effects from individual sectors. Similarly, in the random effects model, a 1 percentage point increase in the growth rate of manufacturing, information, and education and health services sectors might increase the employment growth rate of MSAs by 0.097, 0.026, and 0.051 percentage points, respectively. There was no big difference in the results of the performance of individual sectors between the random effects and the pooled OLS models.

Results of the spatial econometric growth panel model

I also estimated employment growth by spatial lag random effects models. Table 6.10 presents the estimation results. The estimation results for most of the variables were almost the same as the results from the random effects models presented in Table 6.8. Specifically, in the base model without control variables for the performance of individual sectors, competition and educational attainment, which were estimated as insignificant factors by the random effects estimation, had a significant and positive association with the growth rate in the results from the spatial model.

In addition, the geographical dummies turned out to be insignificant in the spatial panel models. It seems that geographical heterogeneity, which was accounted for by the dummy variables in the panel models, might be controlled by the spatially lagged error terms in the spatial model. This led to the change in the significance levels of the geographical dummy variables.

Table 6.10 Spatial Random Effects Model Results for the Growth Panel Model

Variable	Model 1		Model 2	
	Coef	p-value	Coef	p-value
Intercept	-3.566	0.001	-2.756	0.000
Macroeconomic condition dummy				
Economic boom periods (*BOOM*)	2.561	0.000	2.058	0.000
Economic structure variable				
Diversity (*DIV*)[37]	-2.433	0.000	-2.026	0.000
Multiple Specializations (*MSI*)	4.318	0.000	3.528	0.000
Interaction terms: Economic structure variable*BOOM / Competition*BOOM				
*DIV*BOOM*	1.762	0.005	1.693	0.001
*MSI*BOOM*	-5.043	0.000	-4.152	0.000
*COMP*BOOM*	0.204	0.587	-0.020	0.949
General control variable				
Competition (*COMP*)	0.905	0.030	0.593	0.041
Education (*EDUC*)	0.023	0.002	0.027	0.000
Log Population Size (*POP*)	0.023	0.714	0.031	0.438
Geographical dummies				
Midwest region (*MW*)	-0.215	0.241	-0.193	0.096
Northeast region (*NE*)	-0.157	0.422	-0.125	0.311
South region (*S*)	0.098	0.535	0.125	0.213
Performance of Individual sectors				
Natural Resources and Mining (*NRM*)			-0.001	0.369
Construction (*CONS*)			0.094	0.000
Manufacturing (*MANU*)			0.087	0.000
Information (*INFO*)			0.020	0.000
Education and Health Services (*EDH*)			0.038	0.000
Error Variance for Random effects				
Phi (ϕ)	0.164	0.000	0.143	0.000
Spatially Autoregressive Coefficient: Effect of Spatially lagged error term				
Lambda (λ)	0.677	0.000	0.363	0.000
Number of Observations	1412			

Furthermore, in the spatial lag random effects models, the error terms are assumed to be composed of the random effects (regional-specific) and spatially auto-correlated residuals (Baltagi et al., 2007). So with other parameters for the explanatory

[37] Like the general panel models, to avoid the extremely high correlation between the interaction term (*DIV*BOOM*) and the economic boom dummy variable, I centered *DIV* about its mean, in this analysis.

variables in the growth panel model, the maximum likelihood estimation (MLE) for the spatial lag random effects model yielded two more parameter estimations for both the error variance for the random effects (ϕ) and the coefficient for spatial autocorrelation (λ) simultaneously. In the results, the coefficients for the spatial autocorrelation (0.667 and 0.363) were found to be significant in both models, which indicated, even for the short term, the employment growth rate in an MSA is significantly affected by the employment growth in the neighboring MSAs. Additionally, the significant estimation results for the error variance (0.164 and 0.143) for the random effects (ϕ) empirically showed that the model properly controlled the effects of MSA specific factors which usually cause a positive serial correlation in the OLS estimation.

Summary of growth panel model results

Regardless of the estimation methods used or model specifications, the economic structure indicators showed consistent effects on employment growth. Regardless of controlling for the performance of individual sectors or the spillover effects from neighboring MSAs, both the *DIV* and *MSI* had a significant association with the employment growth rate. Specifically, the level of multiple specializations had a positive influence on the employment growth rate while diversity showed a negative effect. However, as presented in Table 6.11, these effects from the structural variables varied by macroeconomic situations. More specifically, the results consistently indicate that the diversity was negatively and significantly associated with the employment growth rate.

Table 6.11 Coefficients of Structural Variables and Interaction Terms in the Growth Panel Models

		DIV	MSI	COMP
Model 1 (Pooled)	Bust	-2.455	5.406	0.467
	Boom	-0.761	0.354	1.112
Model 1 (Random)	Bust	-2.326	5.043	0.518
	Boom	-0.603	-0.356	1.143
Model 2 (Pooled)	Bust	-2.224	4.071	0.578
	Boom	-0.499	0.052	0.643
Model 2 (Random)	Bust	-2.133	3.889	0.578
	Boom	-0.404	-0.271	0.641
Model 1 (Spatial)	Bust	-2.433	4.318	0.905
	Boom	-0.671	-0.725	1.109
Model 2 (Spatial)	Bust	-2.026	3.528	0.593
	Boom	-0.333	-0.624	0.573

As presented in Table 6.11, however, the interaction term between *DIV* and *BOOM* also consistently showed a positive influence on the dependent variable. So it is strongly expected that the negative effect from diversity would drastically decrease during economic boom periods although the magnitudes of the coefficients for the *DIV* are still slightly larger than those for the interaction term. In addition, the effect of multiple specializations was also changed by different macroeconomic situations. On the contrary to the *DIV*, the *MSI* had a positive effect overall while its interaction term consistently indicated a negative coefficient. More interestingly, the magnitudes of the coefficients for both *DIV* and its interaction term showed quite a similar level.[38] This implies that, during an economic boom, multiple specializations would have a very

[38] Most of the results of the linear hypothesis for the estimated parameters could not reject the null hypothesis that the combined effect of both MSI and its interaction term (*MSI*BOOM*) would be equal to zero with very high p-values.

trivial effect on the employment growth rate. Consequently, we may not expect a constant effect from overall economic structure on short-term economic growth because the overall structural effects are highly susceptible to macroeconomic conditions. Especially, compared to an economic bust, the amounts of economic structural effects tend to heavily drop during economic boom periods. This indicates that during an economic boom the economic growth for short-term periods might be less dependent on the overall economic structure. Instead, the high performance of some individual sectors or other factors could contribute more to short-term economic growth.

Among the general control variables, except for one result of the base model by OLS, the level of competition consistently indicated a significant and positive influence on the employment growth rate. The magnitudes of the effects of *COMP* tended to drastically increase during an economic boom when there was no control variable for the performance of individual sectors. However, in results of unrestricted models, the effect of COMP very slightly increased during boom periods (even it decreased by 0.02 in the results of the spatial model). Similar to the competition, except for one case in the base model by random effects estimation, educational attainment also consistently showed a positive effect. However, the initial population size did not have any significant association with the employment growth rate in all models.

For the performance of individual sectors, except for the natural resources and mining sector, the growth rates of all other sectors were consistently estimated to have significant associations with the employment growth rate. However, the growth rate of the natural and mining sector consistently indicated no significant effect. Because the this sector usually represented a tiny portion of employment in MSAs, its performance hardly affected the employment in the overall MSAs even if it showed an extreme growing or declining pattern. Among the effects of the other sectors, the construction and manufacturing sectors showed larger coefficients than the others, which demonstrate their labor-intensive characteristics.

The geographical dummy variables for the Midwest and Northeast regions consistently showed a significant and negative influence on employment growth rates. However, as discussed above, the effects of all geographical dummy variables became insignificant in the spatial lag random effects model. Last, the dummy variable for economic boom periods was consistently estimated to have a positive and significant coefficient, regardless of the types of model or estimation method.

Instability panel models

Similar to the case of growth panel models, two types of models (Models 1 and 2) were specified and estimated. Especially, for Model 2, the growth rates of individual sectors were included to control for the performance of individual sectors. Additionally, the dummy variable for economic boom periods was also included to control for the effects of macroeconomic situations. The results of the instability panel models are presented in Table 6.12.

Results of instability panel model 1

Both the *DIV* and *MSI* were negatively related to employment instability in Model 1. The results suggested that the effects of *DIV* and *MSI* on reducing instability are still strongly pronounced for the short-term periods. Additionally, there was little difference in the results between the pooled OLS and the random effects method in Table 6.12.

Furthermore, the effects of the macroeconomic dummy variable and the interaction terms were also jointly significant in the instability panel models. Specifically, when other factors are fixed and the structural variables have their mean value, the net effect of the macroeconomic dummy indicated a negative value.[39] This means that the MSAs observed less employment instability during the economic boom periods, suggesting that economic instability in regions can reduced by the effects of macroeconomic prosperity. Additionally, the estimation result for the interaction term between *DIV* and *BOOM* showed the same direction, which implies that the effect of diversity on reducing employment instability might be more pronounced during economic boom. Otherwise, the interaction between *MSI* and *BOOM* indicated a positive effect (but the absolute magnitude is still smaller than the main effect of *MSI*), which means the effect of *MSI* on reducing instability decreased during economic boom periods. In addition, the positive effect of the interaction term between competition and the macroeconomic boom dummy variable implies that the positive effect of *COMP* on instability increased during economic boom periods.

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[39] At *DIV*=0 (centered), *MSI*=0.37, and *COMP*=1.04, in the random effects model, the net effect of BOOM, which is the predicted difference between economic boom and bust, was -0.72 + (0.37*0.68) + (1.04*0.13) ≈ -0.33.

Table 6.12 Regression Results for the Instability Panel Model

Variable	Model 1				Model 2			
	Pooled OLS		Random effects		Pooled OLS		Random effects	
	Coef	p-value	Coef	p-value	Coef	p-value	Ceof	p-value
Intercept	-3.633	0.000	-3.791	0.000	-3.724	0.000	-3.883	0.000
Macroeconomic condition dummy								
Economic boom periods (*BOOM*)	-0.724	0.000	-0.744	0.000	-0.611	0.001	-0.613	0.000
Economic structure variable								
Diversity (*DIV*)	-0.374	0.039	-0.337	0.082	-0.385	0.030	-0.364	0.054
Multiple Specializations (*MSI*)	-1.256	0.001	-1.166	0.003	-1.145	0.002	-1.052	0.006
Interaction terms: Economic structure variable*BOOM / Competition*BOOM								
*DIV*BOOM*	-0.662	0.006	-0.719	0.001	-0.684	0.004	-0.731	0.001
*MSI*BOOM*	0.680	0.190	0.787	0.105	0.632	0.213	0.715	0.130
*COMP*BOOM*	0.135	0.353	0.116	0.387	0.192	0.176	0.165	0.206
General control variable								
Competition (*COMP*)	0.336	0.004	0.379	0.003	0.322	0.005	0.376	0.003
Education (*EDUC*)	-0.006	0.001	-0.002	0.253	-0.006	0.000	-0.004	0.047
Log Population Size (*POP*)	-0.057	0.000	-0.058	0.001	-0.057	0.000	-0.057	0.001
Geographical dummies								
Midwest region (*MW*)	-0.063	0.137	-0.048	0.358	-0.090	0.030	-0.077	0.132
Northeast region (*NE*)	-0.284	0.000	-0.282	0.000	-0.300	0.000	-0.301	0.000
South region (*S*)	0.027	0.468	0.045	0.319	0.014	0.689	0.028	0.521
Share of Individual sectors								
Natural Resources and Mining (*NRM*)					0.000	0.343	0.000	0.345
Construction (*CONS*)					-0.012	0.000	-0.012	0.000
Manufacturing (*MANU*)					-0.009	0.001	-0.010	0.000
Information (*INFO*)					-0.005	0.001	-0.005	0.000
Education and Health Services (*EDH*)					-0.001	0.887	-0.002	0.585
Overall R-squared	0.2764		0.2742		0.3148		0.3133	
Number of Observations	1412							

Among the general control variables, as expected by theory, competition consistently revealed a significant effect on increasing employment instability. Otherwise, the negative effect of educational attainment on instability is only significant in the pooled OLS model. As explained earlier, the pooled OLS and the random effects models have different processes for calculating standard errors. So the different calculation process for standard error might cause the discrepancy in the statistical significance for the variable of educational attainment. The initial population size was found to have a negative influence on short-term employment instability, which is consistent with the expectation that a region with a large population size is more likely to be stable than a region with small population size. Specifically, because the *POP* is logged in both estimation methods, the elasticity between the *INSTAB* and *POP* is estimated at about -0.057 - -0.058, indicating that the employment instability indicator decreases by about 0.057 - 0.058 percent with a 1 percent increase in the initial population size.

The geographical dummy variable for the Northeast region is only significant in Model 1. Compared to the West region, the MSAs in the Northeast region experienced less employment instability during these sub-time periods.

Results of instability model 2

Both the *DIV* and *MSI* were consistently rendered significant with the control variables for the performance of individual sectors. These two structural variables were negatively associated with employment instability in MSAs. This consistent pattern in the results indicates that the influences of overall economic structure on employment instability were hardly interfered with by the effects from performances of individual sectors. Furthermore, similar to Model 1, the results of Model 2 also indicated that the MSAs experience less employment instability during economic boom periods.[40] Additionally, the estimation results for the interaction terms are also quite similar to the results of Model 1. Specifically, during economic boom periods, the negative effect of diversity was more reinforced while the negative effect of multiple specializations decreased.

Model 2 also showed that the higher the level of competition, the higher the level of employment instability. Similar to Model 1, the result of the interaction term between *COMP* and *BOOM* indicated that this positive effect of competition also increased during boom periods. In contrast, the initial population size exerted a negative effect on employment instability. In the random effects model, the elasticity between the *INSTAB* and *POP* was estimated at -0.046, indicating a 1 percent increase in the *POP* will decrease the *INSTAB* by 0.046 percent. Moreover, unlike Model 1, educational attainment consistently indicated a significant effect on reducing instability, regardless of the estimation methods. Specifically, in the random effects model, a 1 percentage point increase in *EDUC* is associated with about a 0.004 percent decrease in the employment instability indicator.

For the dummy variables for geographical heterogeneity, the overall estimation results are quite similar with each other. Specifically, the dummy variable for the

[40] In both estimation methods, the net effect of a macroeconomic dummy indicated a negative value of -0.17.

Midwest region gained more statistical significance in Model 2. So, in the results of the pooled OLS, the Midwest region dummy variable, which was insignificant in Model 1, became a highly significant factor in Model 2. Thus, the result of the pooled OLS indicate that, compared to the West region, the MSAs in the Northeast and Midwest region experienced less employment instability during these sub-time periods.

Among the growth rates of individual sectors, three individual sectors – construction, manufacturing, and information – were significantly associated with employment instability for the short-term periods. Specifically, in the random effects model, a 1 percentage point increase in the growth rates of all these sectors will decrease the employment instability indicator by about 0.012, 0.010, and 0.05, respectively. These results are almost the same at the results of the OLS.

Results of the spatial econometric instability panel model

Table 6.13 provides the estimation results of the spatial lag random effects estimation for the instability panel models. The spatially lagged error term was revealed to have a significant effect in both models, which indicates that employment instability in the MSAs for the short-time period is significantly affected by the employment instability of neighboring MSAs.

Table 6.13 Spatial Random Effects Model Results for the Instability Model

Variable	Model 1		Model 2	
	Coef	p-value	Coef	p-value
Intercept	-1.011	0.001	-1.352	0.000
Macroeconomic condition dummy				
Economic boom periods (*BOOM*)	-0.614	0.000	-0.528	0.001
Economic structure variable				
Diversity (*DIV*)[41]	-0.232	0.189	-0.262	0.136
Multiple Specializations (*MSI*)	-1.122	0.002	-1.034	0.004
Interaction terms: Economic structure variable*BOOM / Competition*BOOM				
*DIV*BOOM*	-0.643	0.002	-0.654	0.001
*MSI*BOOM*	0.744	0.092	0.699	0.110
*COMP*BOOM*	0.165	0.176	0.193	0.110
General control variable				
Competition (*COMP*)	0.221	0.058	0.239	0.039
Education (*EDUC*)	-0.004	0.045	-0.005	0.012
Log Population Size (*POP*)	-0.083	0.000	-0.081	0.000
Geographical dummies				
Midwest region (*MW*)	-0.040	0.406	-0.057	0.231
Northeast region (*NE*)	-0.119	0.018	-0.146	0.004
South region (*S*)	0.024	0.559	0.015	0.713
Performance of Individual sectors				
Natural Resources and Mining (*NRM*)			0.000	0.295
Construction (*CONS*)			-0.008	0.000
Manufacturing (*MANU*)			-0.009	0.000
Information (*INFO*)			-0.003	0.026
Education and Health Services (*EDH*)			0.002	0.651
Error Variance for Random effects				
Phi (ϕ)	0.203	0.000	0.212	0.000
Spatially Autoregressive Coefficient: Effect of Spatially lagged error term				
Lambda (λ)	0.495	0.000	0.450	0.000
Number of Observations	1412			

Among two structural variables, the effect of diversity, which was highly significant in the random effects and pooled OLS models, became marginally significant in the spatial model. Specifically, with a one-sided probability, the coefficient of *DIV*

[41] Like the general panel models, to avoid the extremely high correlation between the interaction term (*DIV*BOOM*) and the economic boom dummy variable, I used the *DIV*, which has been centered about its mean, in this analysis.

was significant at a 0.10 level in both models. However, the effect of *DIV* still showed a negative sign, which means that diversity still helped to enhance the employment instability in MSAs. Additionally, the level of multiple specializations was consistently estimated to have a significant and negative effect on instability. This indicates that the effect of *MSI* on promoting stability was hardly affected by controlling for the spillover effect from neighboring MSAs.

Regarding the interaction terms, the interaction term between *DIV* and *BOOM* had a significant and negative influence although the *DIV* itself was marginally significant. So, the negative effect of diversity was more presented during economic booms, which was very consistent with the results of the general panel models. Additionally, the estimation results for other interaction terms showed substantially similar patterns with the results of the general panel models.

Moreover, in the case of base model estimation, the effect of *EDUC*, which was insignificant in the random effects model, became highly significant in the spatial lag random effects model. As repeatedly mentioned, this difference might be explained by the dissimilarity in computing standard errors of the two models – the random effects and the spatial lag random effects models. Moreover, among the geographical dummy variables, only the one for the Northeast region was only discovered to have a significant effect. Last, the estimation results for the performance of individual sectors or the macroeconomic boom dummy variable were very similar to the results of the general panel models.

Summary of instability panel model results

The results of the instability panel models consistently showed that both the variables of diversity and multiple specializations were significantly associated with reducing the employment instability for the short-term time periods.

Table 6.14 Coefficients of Structural Variables and Interaction Terms in the Instability Panel Models

		DIV	MSI	COMP
Model 1 (Pooled)	Bust	-0.374	-1.256	0.336
	Boom	-1.036	-0.576	0.471
Model 1 (Random)	Bust	-0.337	-1.166	0.518
	Boom	-1.056	-0.379	0.634
Model 2 (Pooled)	Bust	-0.385	-1.145	0.322
	Boom	-1.069	-0.513	0.514
Model 2 (Random)	Bust	-0.364	-1.052	0.376
	Boom	-1.095	-0.337	0.541
Model 1 (Spatial)	Bust	-0.232	-1.122	0.221
	Boom	-0.875	-0.378	0.386
Model 2 (Spatial)	Bust	-0.262	-1.034	0.239
	Boom	-0.916	-0.335	0.432

Furthermore, as presented in Table 6.14, the estimation results of the interaction terms showed that the effects of the overall structure on instability were not drastically affected by the macroeconomic situations. The results showed that the effect of diversity on reducing instability tended to strengthen more during economic boom periods. Similarly, the effect of competition on increasing instability also increased over boom periods. Otherwise, the results indicated that the effect of multiple specializations on reducing instability were likely to decrease during boom periods.

Among the general control variables, the results indicated that competition consistently increased instability while the initial population size was continually estimated to have a negative effect. Moreover, in most of the results, educational attainment was also repeatedly observed to have a negative association with instability. For the geographical dummy variables, most results indicated that, compared to the West region, the MSAs in the Northeast region observed less instability for the short time periods. Last, all the results significantly suggested that the employment in MSAs is likely to be more stable during economic boom periods.

The growth rates of three individual sectors – construction, manufacturing, and information – were consistently associated with reducing the employment instability for the short-term periods. One notable fact was that, except for the growth rate of the information sector for period 1 (from 1998 to 2000), the other two sectors were selected as the ones most declining. This means the less declines in these sectors, the more stable the overall economy. Even the information sector also showed a declining pattern since period 2. However, the growth rate of the most growing sector (education and health services) showed a positive sign but it was statistically insignificant. Thus, these results indicate that the performance of declining sectors might be more related to the decrease in employment stability.

6.3 Concluding Remarks

This chapter examines the empirical association between the economic structure and regional economic performance. For growth, the main results consistently revealed that, among the two structural indicators, only the *MSI* was significantly associated with accelerating the economic growth in MSAs. Instead, diversity had a negative influence on growth. Otherwise, for stability, the results showed that both *MSI* and *DIV* are simultaneously related to the reduction in employment instability. Combining these results, multiple specializations in the overall economic structure is a significant factor that can help to accomplish both economic growth and stability at the same time.

A second important issue of this study is whether the relationship between the economic structure and performance holds for different macroeconomic situations. To answer this question, I conducted panel analyses with a control variable for the economic boom periods. The main finding from the panel analyses was that the effects of diversity and multiple specializations on growth might vary in different macro-economic situations. Specifically, the results indicated that, in an economic boom, the negative effect of diversity moderately decreased and the positive effect of multiple specializations also collapsed to zero. On the contrary, in the case of employment instability, the effects of overall economic structure and instability consistently had a very solid association which was hardly affected by the macroeconomic situations. Even the negative effect of diversity tended to be more reinforced during economic boom periods. Furthermore, multiple specializations also consistently indicated a negative effect over boom periods although the magnitude of this negative effect decreased.

CHAPTER VII

CONCLUSION

7.1 Summary of Findings

This study investigates the role of economic structure in determining economic performance in regions. When measuring regional economic performance, this study not only considered the perspective of economic growth, but also took into account stability. So, two cross-sectional models – one for growth and another for instability – were estimated for the MSAs during the period from 1998 to 2010. Furthermore, panel analyses based on the short-time periods were also conducted to examine whether the relationship between the economic structure and performance holds during economic boom and bust periods.

7.1.1 Major Findings

Two primary research hypotheses, which are related to each economic structural indicator, guided the analysis of economic growth. The first one is that a region with a more diversified economic structure is more likely to have higher economic growth. The empirical results denied this hypothesis, finding that a higher level of diversity adversely affects employment growth and the negative effect is statistically significant. These findings provided evidence supporting the expectation by Porter (1998) or Marshall-Arrow-Romer that specialization can promote economic growth, which are consistent with some of previous studies by Henderson et al. (1995) and van Oort and Stam (2006).

However, my findings still differ from the results of other previous studies that emphasized the role of economic diversity in economic growth. The one plausible explanation is that the evidence provided by these diversity supporters are somewhat outdated because many of these studies were based on old data from the 70s to the 90s (i.e., Glaeser et al. [1992] or Wagner and Deller [1998]). However, the data used in this dissertation was based on a recent time period from 1998 to 2010. This implies that the current regional economy has stood upon a basis that already fully utilized the positive effect of economic diversity. Hence, during the recent time period in which this study was conducted, diversity had no more positive effects that could contribute to producing jobs in regions.

The second hypothesis posited that regions with a higher portion of specialized sectors are more likely to show a higher level of economic growth. The concept of multiple specializations is only theoretically mentioned in previous literature, but was not empirically tested. This study, for the first time, attempted to examine the effects of multiple specializations on economic performance by developing a new indicator for empirically measuring the level of multiple specializations. The empirical results in this study consistently uphold the above hypothesis about the effects of multiple specializations on economic growth. In most growth models, the effect of multiple specializations is empirically estimated to have a positive influence on the employment growth rate in MSAs. Combining the above results, among these two characteristics of economic structure, economic growth in regions is more positively affected by multiple specializations than diversity.

Similar to the growth model, two primary research hypotheses also directed the analysis. The first is that a regional economy with a high level of diversity is more likely to be stable. The second is that a regional economy with a the higher portion of specialized sectors is also expected to be stable. The results of this research largely support both hypotheses, finding consistent and significant influences of both diversity and multiple specializations on enhancing employment stability. These findings strongly agree with the previous evidence and also suggest that specialization can cause regional economies to more likely experience severe economic fluctuations.

Consequently, I can answer the research question, *Which economic structure helps regions accomplish both economic growth and stability simultaneously?* by synthesizing the results of both the growth and instability analyses. The results of both growth and instability models suggest that a region with a multiply specialized economic structure is more likely to experience both growth and stability at the same time.

One important extension to the above analyses was conducted to examine one more research question of whether the associations between economic structure and performance hold for different macroeconomic situations. In the growth panel models, the effects of diversity and multiple specializations on the employment growth rate varied across different macroeconomic situations. The amount of these effects from both diversity and multiple specializations significantly decreased during economic boom periods. Specifically, the magnitude of the negative effect from diversity was drastically decreased during economic boom periods. Moreover, the combined effect of multiple specializations and its interaction term became almost zero during economic boom periods. This means that we can hardly expect a positive effect of multiple specializations on growth during an economic boom. On the other hand, in the results of the instability panel models, it was consistently observed that both diversity and multiple specializations contributed to employment stability, regardless of the macroeconomic situations. More specifically, the results showed that the effect of diversity on enhancing the employment stability tended to be more pronounced during an economic boom. The negative effects of multiple specializations on instability did not indicate a significant difference during economic boom periods.

Comparing these results from the panel models to the results from the overall models, in terms of economic stability, both overall and panel models yielded almost the same results. The MSAs with higher levels of both diversity and multiple specializations were expected to experience higher levels of employment stability. However, in terms of economic growth, although the effects of diversity and multiple specializations showed the same directions in both overall and panel models, the magnitude of these effects were significantly changed by macroeconomic conditions. As mentioned above, the growth panel model showed that the effects of diversity and multiple specializations considerably decreased during economic boom periods. So we may not expect significant effects from economic structure during a period of macroeconomic prosperity.

In addition, there is another reason that can explain the difference in the results between overall and panel growth models. As pointed by Wagner and Deller (1998), it usually requires a long time for economic structure (diversity or multiple specializations) to affect economic growth. So, although it depends on the case, the period of two to three years, which was used in the panel models, might be too short a time to consistently observe the effects of overall economic structure on economic growth. Hence, besides the macroeconomic situations, this issue of a short time period can also be another implicit reason that brought inconsistent results for the effects of economic structure in the growth panel model.

7.1.2 Additional Findings

Competition was found to be a determining factor for regional economic performance. The positive effect of competition was consistently observed as significant in the growth models. On the other hand, in the instability models, competition was consistently recognized as an important factor that can increase the instability. This suggests that the effects of a competitive economic condition is very significant for both growth and stability, while both the goals of growth and stability will hardly be reached simultaneously by promoting competition.

Additionally, the overall models also showed that educational attainment is also significantly associated with both growth and instability. In the estimation results, as expected from the previous literature, the MSAs with a higher portion of highly educated people indicated a higher growth rate and a lower level of instability at the same time. Therefore, like multiple specializations, educational attainment is another factor that can positively affect both growth and stability at the same time.

This study found that both growth and instability have a path dependency over time. In the results, past growth and instability were strong predictors for growth and instability during the study period, respectively. Furthermore, I also found some cross effects from these past performance indicators. Specifically, in the instability models, past economic growth was consistently estimated as a significant factor that increased the instability.

In all the spatial models, the spatially lagged variable was estimated to have a statistically significant effect on both growth and instability. This means that, in addition to the specified explanatory variables, the effects from economic performance – growth and stability – of neighboring regions was also another important determinant of regional economic performance. The results suggested that considering the spatial effect might be critical to minimize the bias issue for research based on spatial data, although, like this study, using the spatial econometric model does not significantly change the estimation results.

7.2 Policy Implications

> *"Diversification policies should be viewed as the long-run envelope of the region's short-run efforts. Long-run policy can be viewed as promoting stability with growth. As stability and diversity increase, so should the potential for growth. ... The apparent contradictory goals (growth and stability) and policies (diversification and specialization) can be pursued simultaneously and consistently" (Wagner & Deller, 1998, p.542)*

The policies or strategies for regional economic development should be built on solid empirical studies. For this purpose, regional scientists or economists have historically suggested or promoted the policy of adjusting economic structure in order to accomplish economic objectives in regions. As noted by Jacobs (1969), economic diversity in cities is the most necessary condition for producing innovative outcomes through knowledge spillovers. At the same time, it is also widely accepted that a region with a higher diversity level becomes less sensitive to economic fluctuations and hence shows a higher level of economic stability (Richardson, 1969). Therefore, policymakers have believed that both economic growth and stability can be simultaneously promoted by economic diversification (Attran, 1987; Malizia & Ke, 1993). Thus, in many localities, recruiting or attracting firms by various types of incentives such as tax abatement is still the most popular policy tool for local governments to use to enhance their economic growth by diversifying their economic bases (Bartik, 1991; Wasylenko, 1997).

However, the results of this study suggested that fostering economic diversity might not be more effective for promoting economic growth in MSAs. According to Donegan et al. (2008), the recent efforts to diversify economic structure tended to be concentrated on attracting various high-technology industries because the high technology field is expected to produce more innovative outcomes by interaction among the different sectors within this field. However, in terms of employment, this effort of diversifying the high-technology sector might be inadequate for creating jobs because the nature of the high-technology sector is not labor intensive. If so, is specialization a better option for regional economies?

According to the basic theory, the comparative advantages based on economic specialization can drive economic growth in regions (Marshall, 1890). Building the clusters is the most representative development strategy based on economic specialization (Donegan, et al., 2008). However, previous literature also warned that economic instability can be aggravated by specialization. For these reasons, in terms of specialization, it can be difficult for policymakers to pursue a course between the two contradictory goals of economic growth and stability (Wagner & Deller, 1998). As argued by Spelman (2006), economic stability is as influential as economic growth in constituting regional economic performance. Hence, although there are a great many benefits from specialization on economic growth, policymakers should not pursue the specialization strategy and ignore economic instability.

As suggested by this study, we should focus on multiple specializations. According to the empirical results of this study, policymakers can attempt to pursue both growth and stability simultaneously by developing a multiply specialized economic structure. In terms of economic structure, the focus of development strategy should be shifted from simple diversification to building multiple specializations. In practice, building or developing various types of clusters can be the most appropriate strategy for pursuing economic development through multiple specializations. More specifically, if some regions already have a certain level of diversity in their economic structure, the local governments for those regions can select several potential sectors and enhance these selected sectors by promoting niche creation from existing industries (Frenken et al., 2007).

However, if the economies of regions already suffer from a lack of diversity, the local governments should promote both diversity and specialization together. As explained by Desrochers and Sautet (2008), the diversified economic structure can work as a necessary precondition or foundation for multiple specializations in regions. Moreover, Malizia and Feser (1999, p. 92) argued that "economic diversity can only be defined operationally as the presence of multiple specializations." In this context, diversification should be processed based on the full consideration of specialization. So, rather than spending a great deal of a budget to import "advanced sectors" or "popular sectors," the local governments should focus instead on recruiting the sectors that have many linkages with the indigenous comparative advantages in their regions. By connecting the imported sectors with these indigenous strengths, the locality can develop multiple specializations much more efficiently than relentlessly attracting and developing a brand-new sector.

In addition, the panel models based on the short time periods yielded consistent results for the relationships between economic structure and stability, suggesting that any strategy of developing diversity or multiple specializations can help to enhance economic stability in regions, regardless of macroeconomic situations. However, the results for the relationship between economic structure and growth can vary in different macroeconomic situations. Specifically, the results showed that the effects of overall economic structure might be less effective during economic boom periods. As Wager and Deller (1998) pointed out, instead of overall economic structure, developing or investing in several selected sectors, which mostly fit with the macroeconomic situation or trend, might be the best strategy for economic growth in the short-run. However, this growth-oriented strategy of targeting a few specific sectors can be in a trap, called “job is done” or “growth is done” syndrome (Wagner & Deller, 1998). This can be dangerous in two ways. First, as these selected sectors or industries mature or develop, the driving forces for economic growth from these sectors will also decrease. Second, if the performances of the targeted sectors are bad, the economy of the region can be severely and adversely affected by the failure of these sectors. As a result, the economic condition of that region might be worse off than before the strategy of specializing in a few targeted sectors was implemented. Therefore, the policies related to economic structure should be designed and implemented in the long-run view. For example, as I mentioned above, building multiple types of clusters will definitely increase the level of diversity or multiple specializations but will need more time to produce the effects of multiple clusters on regional economic performance. However, as suggested by the results of this study, multiple specializations consistently indicated a positive effect on growth in the overall model based on a long-term period. Hence, the policies for the overall economic structure are still worth pursuing although we cannot immediately see the effects of diversity or multiple specializations.

7.3 Limitations and Further Research Directions

This study has several limitations that may hinder the validity of this research. First, because of data consistency and feasibility, this study was only based on the period from 1998 to 2010. However, the indicators – growth rates and instability indicators – related to regional economic performance are very dependent on the time period in which they are calculated. In addition, the boom and bust of economic sectors consisting of overall economic structures may be different in other time spans. Therefore, by extending the research time span and comparing the various different time periods, the results of this study can be enriched.

The second limitation is the geographical unit of analysis in this study. This research was basically analyzed by using the Metropolitan Statistical Areas (MSAs) as the unit of analysis. Even if MSAs were the most appropriate spatial unit for regional economic function, the boundaries of MSAs do not always coincide with the boundaries of the effects of economic structure or economic performance. Additionally, there can be other factors based on different spatial scales that may affect economic performance. Specifically, because all counties in one MSA do not equally contribute to the economic performance of that MSA, a county-level study might be needed to investigate the intra MSAs dynamics for identifying the spatial pattern of economic performance within each MSA.

Third, the effects of economic structure and other factors, which were estimated in this study, have a potential bias problem. After I controlled for possible other variables affecting economic growth and stability, there can still be other factors which are significantly related to regional economic performance. Besides, there are still other concepts, which are theoretically recognized as influencing factors, but are not empirically captured by specific variables. Hence, the results of this research can be improved by adding appropriate control variables such as policy effects. Furthermore, although this study found that the association between economic structure and growth might be affected by the macroeconomic situations, it did not specifically identify the factors which can consistently affect the short-term economic growth. Therefore, the question remains: Besides overall economic structure, which factor can consistently affect economic growth for the short-term period, regardless of the types of macroeconomic situations? Investigating the regional specific industrial fortune at the detail level, the roles of development institutions, and other amenities for the labor force may lead to explanations for this future research agenda.

Fourth, when considering the relationships between regional economic performance and macro-economic conditions, this study did not specify any specific internal or external perturbations. Instead, it was based on the general economic fluctuations of regions. As a future research, this study could be extended to identify various socio-economic factors related to constructing a regional economic resiliency against natural disasters. In terms of empirical perspectives, the concept of economic resiliency still has many black boxes which need to be investigated. Therefore, by using specific shocks, this research can make a contribution to empirically analyzing the concept of economic resiliency and its related factors. Furthermore, the results from these analyses may provide more detailed regional economic development strategies.

Finally, when measuring regional economic performance, this study only considered the factor of employment among various indicators related to regional economic performance such as gross domestic product or personal income. So, this research may be open to the application of different types of economic performance indicators.

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APPENDIX A. LIST OF 3-DIGIT NAICS INDUSTRIES

Table A.1 The List if 3-Digit NAICS Industries

Codes	Industry
113	Forestry and logging
114	Fishing, hunting & trapping
115	Agriculture & forestry support activities
211	Oil & gas extraction
212	Mining (except oil & gas)
213	Mining support activities
221	Utilities
233	Building, developing & general contracting
234	Heavy construction
235	Special trade contractors
311	Food manufacturing
312	Beverage & tobacco product manufacturing
313	Textile mills
314	Textile product mills
315	Apparel manufacturing
316	Leather & allied product manufacturing
321	Wood product manufacturing
322	Paper manufacturing
323	Printing & related support activities
324	Petroleum & coal products manufacturing
325	Chemical manufacturing
326	Plastics & rubber products manufacturing
327	Nonmetallic mineral product manufacturing
331	Primary metal manufacturing
332	Fabricated metal product manufacturing
333	Machinery manufacturing
334	Computer & electronic product manufacturing
335	Electrical equip, appliance & component manufacturing
336	Transportation equipment manufacturing
337	Furniture & related product manufacturing
339	Miscellaneous manufacturing
421	Wholesale trade, durable goods

Table A.1 Continued

Codes	Industry
422	Wholesale trade, nondurable goods
441	Motor vehicle & parts dealers
442	Furniture & home furnishing stores
443	Electronics & appliance stores
444	Building material & garden equip & supply dealers
445	Food & beverage stores
446	Health & personal care stores
447	Gasoline stations
448	Clothing & clothing accessories stores
451	Sporting goods, hobby, book & music stores
452	General merchandise stores
453	Miscellaneous store retailers
454	Non-store retailers
481	Air transportation
483	Water transportation
484	Truck transportation
485	Transit & ground passenger transportation
486	Pipeline transportation
487	Scenic & sightseeing transportation
488	Transportation support activities
492	Couriers & messengers
493	Warehousing & storage
511	Publishing industries
512	Motion picture & sound recording industries
513	Broadcasting & telecommunications
514	Information & data processing services
521	Monetary authorities - central bank
522	Credit intermediation & related activities
523	Security, commodity contracts & like activity
524	Insurance carriers & related activities
525	Funds, trusts, & other financial vehicles (part)
531	Real estate
532	Rental & leasing services
533	Lessors of other nonfinancial intangible asset
541	Professional, scientific & technical services
551	Management of companies & enterprises
561	Administrative & support services

Table A.1 Continued

Codes	Industry
562	Waste management & remediation services
611	Educational services
621	Ambulatory health care services
622	Hospitals
623	Nursing & residential care facilities
624	Social assistance
711	Performing arts, spectator sports, & related industries
712	Museums, historical sites & like institutions
713	Amusement, gambling & recreation industries
721	Accommodation
722	Food services & drinking places
811	Repair & maintenance
812	Personal & laundry services
813	Religious, grant-making, civic, prof & like organizations

Source: http://www.census.gov/econ/cbp/download/naics.txt

APPENDIX B. MORAN'S I TEST FOR DETECTING SPATIAL AUTOCORRELATION

The Moran's *I* test is the most widely used specification test for spatial autocorrelation, and was first developed by Moran (1948). To conduct the Moran's *I* test, there is a need to define the neighbors by using a spatial weights matrix. Although there are various types and ways to generate a spatial weights matrix, in this study I have to use a distance-inversed type because the analytic unit, MSA, is spatially discontinuous in space. Thus, according to Cliff and Ord (1981), the test statistic from Moran's *I* test, *I*, is indicated as the following matrix notation:

$$I = \frac{\hat{\varepsilon}^T W \hat{\varepsilon}}{\hat{\varepsilon}^T \hat{\varepsilon}}$$

where $\hat{\varepsilon}$ is a vector of residuals from the regression analysis and W is a row-standardized spatial weights matrix.

If there is no spatial effect in the residuals, there is no need to use spatial econometric models. While the Moran's *I* test has an advantage in pointing out the presence of spatial autocorrelation in the estimation results, it also has one limitation in that it cannot identify which type of spatial econometric models, e.g., spatial lag or spatial error, is appropriate for a certain case (Anselin & Rey, 1991).

APPENDIX C. SPATIAL LAG MODEL VERSUS SPATIAL ERROR MODEL

The general spatial econometric form is specified by the following:

$$
\begin{aligned}
y &= \rho W y + X\beta + \varepsilon \\
\varepsilon &= \lambda W \varepsilon + u, \qquad u \sim \mathrm{N}(0, \sigma^2 I)
\end{aligned}
$$

where y is a vector of the dependent variable; W is a spatial weights matrix; X is a vector of the independent variables; u is a vector of residuals; ρ is a coefficient of a spatially lagged dependent variable; β is a vector of the coefficients for non-weighted independent variables; ε is a vector of error terms; λ is a coefficient in a spatial autoregressive structure for error terms; and u is a vector of residuals.

When estimating spatial econometric models, the OLS estimator is inappropriate because the estimation results from the OLS for spatial econometric models are biased and inefficient (Anselin & Bera, 1998). Instead, the maximum likelihood estimation (MLE) is used to estimate the spatial econometric model. The MLE is used to find parameters that maximize the joint probability of an observed dependent variable. The underlying condition is that the parametric distribution of the observed dependent variable should be known (Greene, 2003). In the estimation process, the maximum likelihood estimator is obtained by maximizing log-likelihood function of spatial econometric models. The parameters in the general spatial econometric model are estimated by the following log-likelihood function (Anselin, 1988, p. 63):

$$
\begin{aligned}
\ln L = &-\frac{N}{2}\ln(2\pi) - \frac{N}{2}\ln\sigma^2 + \ln|I - \rho W| + \ln|I - \lambda W| \\
&-\frac{1}{2\sigma^2}\left[(I - \rho W)y - X\beta\right]^T (I - \lambda W)^T (I - \lambda W)\left[(I - \lambda W)y - X\beta\right]
\end{aligned}
$$

Based on this general model, the following specific models, which are the most frequently used in empirical studies, are derived by placing constraints on the general model.

First, when the main interest is to assess the presence and strength of spatial interaction, the spatial lag model ($\rho \neq 0 \; and \; \lambda = 0$) is proper. In this model, the spatial dependence implicitly indicates that the observed value in one specific area can be determined by those of other areas. So, the spatial lag model is more appropriate to test the existence of spatial externalities or spillover effects (Anselin, 1988). The basic form of the spatial lag model is:

$$y = \rho W y + X\beta + u$$

where y is a vector of the dependent variable; W is a spatial weights matrix; X is a vector of the independent variables; u is a vector of residuals; ρ is a coefficient of a spatially lagged dependent variable; and β is a vector of the coefficients for non-weighted independent variables. In the estimation process, the spatial lag term is treated as a type of endogenous variable, which is always correlated with the error terms. Thus, the estimation method is focused on accounting for this endogeneity problem. To overcome this endogeneity issue, the spatial lag model is estimated by the following log-likelihood function:

$$\begin{aligned} \ln L = & -\frac{N}{2}\ln\left(2\pi\right) - \frac{N}{2}\ln\sigma^2 + \ln\left|I - \rho W\right| \\ & -\frac{1}{2\sigma^2}\left[(I - \rho W)y - X\beta\right]^T\left[\left(I - \lambda W\right)y - X\beta\right] \end{aligned}$$

The ML estimator for β is estimated by using the first order condition for maximizing the above log-likelihood function. So, the ML estimator is (Anselin, 1988, pp. 61-64):

$$\tilde{\beta} = \left(X^T X\right)^{-1} X^T \left(I - \rho W\right) y$$

Second, if the main concern is correcting the biasing effects from spatial autocorrelation in the spatial data, the spatial error model ($\rho = 0 \; and \; \lambda \neq 0$) is more appropriate. In the spatial error model, the spatial autocorrelation or dependence is treated as measurement errors such as ignored or unknown spillover effects from other spatial units (Anselin & Bera, 1998). So, the spatial error model is formally indicated in the following two stage form:

$$\begin{aligned} y &= X\beta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + u \end{aligned}$$

where y is a vector of the dependent variable; W is a spatial weights matrix; X is a vector of the independent variables; ε is a vector of error terms; λ is a coefficient in a spatial autoregressive structure for error terms; and u is a vector of residuals. Because of the spatial autoregressive property in error terms, the error term is indicated as a non-spherical form, which induces the heteroskedasticity problem in the error term. Therefore, the estimation method is focused on dealing with the problem of non-constant error. The spatial error model is estimated by the following log-likelihood function:

$$\begin{aligned} \ln L = &-\frac{N}{2}\ln\left(2\pi\right) - \frac{N}{2}\ln\sigma^2 + \ln\left|I - \lambda W\right| \\ &-\frac{1}{2\sigma^2}\left(y - X\beta\right)^T \left(I - \lambda W\right)^T \left(I - \lambda W\right)\left(y - X\beta\right) \end{aligned}$$

The ML estimator for β is estimated by using the first order condition for maximizing the above log-likelihood function. So the ML estimator is:

$$\tilde{\beta} = \left[X^T (1-\lambda W)^T (1-\lambda W) X \right]^{-1} X^T (1-\lambda W)^T (1-\lambda W) y$$

APPENDIX D. THE LAGRANGE MULTIPLIER TEST

When the spatial autocorrelation is verified by Moran's *I* test, the Lagrange Multiplier (LM) tests are usually performed to select the appropriate spatial econometric model between the spatial lag and the spatial error model. First, the LM-lag test, which was first suggested by Anselin (1988), is conducted to check the presence of spatial autocorrelation in the dependent variable. So, the null hypothesis for the LM-lag test is that there is no spatial autocorrelation in the dependent variable ($H_0 : \rho = 0$). And the LM-lag statistic, $LM - lag$, takes the following form:

$$LM - lag = \frac{\hat{\varepsilon}^T Wy / \hat{\sigma}^2}{RJ_{\rho-\beta}}$$

where $\hat{\varepsilon}$ is a vector of residuals; $\hat{\sigma}^2$ is $\frac{\hat{\varepsilon}^T \hat{\varepsilon}}{N}$; W is a spatial weights matrix; y is the dependent variable; and $RJ_{\rho-\beta}$ is $T + (WX\hat{\beta})^T M (WX\hat{\beta}) / \hat{\sigma}^2$ with T as $tr(W^T W + W^2)$; a spatially lagged projected value ($WX\hat{\beta}$); and the projection matrix (*M*). Additionally, this statistic follows a χ^2 distribution.

Second, the LM-error test, which was first suggested by Burridge (1980), tests the spatial error autocorrelation. The null hypothesis for the LM-error test is that there is no spatial autocorrelation in the error term ($H_0 : \lambda = 0$). The LM-error statistic, $LM - error$, takes the following form:

$$LM - error = \frac{1}{T}\left(\frac{\hat{\varepsilon}^T W \hat{\varepsilon}}{\sigma^2}\right)^2$$

where $\hat{\varepsilon}$ is a vector of residuals; $\hat{\sigma}^2$ is $\frac{\hat{\varepsilon}^T \hat{\varepsilon}}{N}$; W is a spatial weights matrix; and T is $tr(W^T W + W^2)$. This statistic also follows a χ^2 distribution.

If the LM-lag statistic is statistically significant while the LM-error is not, then using the spatial lag model is the likely option, and vice versa. If both statistics are significant, the statistic that has the largest value indicates the more appropriate model (Florax & De Graaff, 2004). Also, as more specific methods to select an appropriate model for this case, robust LM-lag and robust LM-error tests can be used (Florax & Nijkamp, 2004). The major difference between robust LM-lag or error and LM-lag or error tests is that the robust approaches test the same hypotheses with the consideration for local spatial dependence. For example, while the LM-error test is conducted based on the assumption that there is no spatial lag dependence, the robust LM-error test is performed considering the presence of spatial lag dependence (Osland, 2010). Therefore, when both LM statistics are significant, the one which indicates the higher robust LM statistic value can be the more appropriate model.

APPENDIX E. ESTIMATION OF RANDOM EFFECTS MODEL

The following estimation process of a panel model is made based on two literatures.[42] A panel model can be defined by the following with an unobserved effect (e.g., region specific factor), a_i , that has zero mean and no correlation with other explanatory variables.

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \ldots + \beta_n x_{itn} + a_i + \varepsilon_{it}$$

In the RE (Random Effect) estimation, a_i is regarded as one part of the composite error term, v_{it}. So, the above equation is modified by this composite error term:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \ldots + \beta_n x_{itn} + v_{it}$$

$$v_{it} = a_i + \varepsilon_{it}$$

Because the composite errors in all time periods have a_i in common, the composite error, v_{it}, has to be serially correlated across time. By the following two assumptions of the idiosyncratic errors ε_{it} :

(1) $E(\varepsilon_{it}^2) = \sigma_\varepsilon^2$ where σ_ε^2 is the variance of idiosyncratic errors

(2) $E(\varepsilon_{it}\varepsilon_{is}) = 0$, all $t \neq s$

the variances and covariances of the composite error term can be derived:

$$E(v_{it}^2) = E(a_i^2) + 2E(a_i\varepsilon_{it}) + E(\varepsilon_{it}^2)$$

[42] Wooldridge (2002, 2009)

The above equation can be collapsed into the following equation by the assumption of the RE model that a_i is uncorrelated with all explanatory variables.

$$E(v_{it}^2) = \sigma_a^2 + \sigma_\varepsilon^2 \quad \text{where } \sigma_a^2 = E(a_i^2)$$

Additionally, for all $t \neq s$

$$E(v_{it}v_{is}) = E[(a_i + \varepsilon_{it})(a_i + \varepsilon_{is})] = E(a_i^2) = \sigma_a^2$$

Because of this covariance, σ_a^2, the RE model automatically the assumption of homoscedasticity. Under the assumption of homoscedasticity, the variance of error is constant with the same value of σ_ε^2. However, in the RE model, the variance of composite error indicates $\sigma_a^2 + \sigma_\varepsilon^2$. To deal with this violation, the RE model is estimated by the GLS (Generalized Least Square) with the weight λ which is defined by the following:

$$\lambda = 1 - [\sigma_\varepsilon^2 / (\sigma_\varepsilon^2 + T\sigma_a^2)]^{1/2}$$

$$\text{where } |\lambda| < 1$$

With this weight, the panel with the composite error can be transformed by:

$$y_{it} - \lambda \overline{y}_i = \beta_0(1-\lambda) + \beta_1(x_{it1} - \lambda \overline{x}_{i1}) + ... + \beta_n(x_{itn} - \lambda \overline{x}_{in}) + (v_{it} - \lambda \overline{v}_i)$$

Therefore, the parameters in the RE model is estimated by estimating the above transformed equation with the OLS.

APPENDIX F. SPATIAL RANDOM EFFECTS MODEL

Following Baltagi et al. (2007), suppose a panel model is defined by the following:

$$y_{it} = X_{it}\beta + u_{it}$$

where i indicates the number of cross-sectional unit and t indicates the time periods. The composite error term, u_{it}, is assumed to be composed of regional random effect (a_i) and spatially auto-correlated error term that are specified by the following vector form:

$$u_t = a + \varepsilon_t \text{ and } \varepsilon_t = \lambda W \varepsilon_t + v_t$$

In addition, the remainder error term (v_t) is also assumed to be specified by a first-order serially auto-correlated process.

$$v_t = \rho v_{t-1} + e_t \text{ with } e_{it} \sim N(0, \sigma_e^2), \quad v_{i0} \sim N(0, \sigma_e^2/(1-\rho^2))$$

λ ($|\lambda| < 1$) is a coefficient of spatial autoregressive term. ρ ($|\rho| < 1$) is a coefficient of the time-wise serial correlation. Additionally, W is a spatial weight matrix with zero diagonal elements. The equation of spatially auto-correlated error term can be rewritten by:

$$\varepsilon_t = (I_N - \lambda W)^{-1} v_t = B^{-1} v_t \text{ where } B = I_N - \lambda W$$

Finally, the composite error term, u ,can be expressed as the following matrix notation:

$$u = (\iota_T \otimes I_N)a + (I_T \otimes B^{-1})v$$

where ι_T is a vector of ones and I_N is an identity matrix with dimension N. Similarly, I_T indicates an identity matrix with dimension T.

Based on the above composite error term, the variance-covariance matrix of spatial panel model is derived. Using the variance-covariance matrix of spatial panel model, the following log-likelihood function, which can be used for estimating the parameters in the panel model, is induced.

$$L(\beta,\sigma_e^2,\rho,\lambda) = C + \frac{1}{2}N\ln(1-\rho^2) - \frac{1}{2}\ln\left|d^2(1-\rho)^2\sigma_\mu^2 I_N + \sigma_e^2(B^T B)^{-1}\right|$$
$$-\frac{N(T-1)}{2}\ln(\sigma_e^2) + (T-1)\ln|B| - \frac{1}{2}u^{*T}\Omega^{*-1}u^*$$

where $u^* = (1-\rho)(\iota_T^\alpha \otimes I_N)\mu + (C \otimes B^{-1})v$ with $\iota_T^\alpha = (\alpha, \iota_{T-1}^T)$ and $\alpha = \sqrt{(1+\rho)/(1-\rho)}$

where $\Omega^* = E(u^* u^{*T})$

By using the above likelihood function, we can estimate the parameters of explanatory variables, spatial autocorrelation, serial error correlation, and regional random effect at the same time.

APPENDIX G. RESULTS OF THE MORAN'S I TESTS AND THE LM TESTS

The spatial weight matrix based on the inverse of distance squared is basically employed.

Table G.2 Results of the Moran's I Test for Growth Models

Models	Results	
	Moran I statistic	p-value
Model 1	0.1296	0.00
Model 2	0.0651	0.01

Table G.3 Results of the LM Test for Growth Models

Types of test statistics	Model 1		Model 2	
	Statistic	p-value	Statistic	p-value
LM error	18.71	0.00	4.72	0.03
LM lag	31.57	0.00	21.41	0.00
Robust LM error	1.77	0.18	4.81	0.03
Robust LM lag	14.62	0.00	21.49	0.00
Selected model type	Spatial lag model		Spatial lag model	

Table G.4 Results of the Moran's I Test for Instability Models

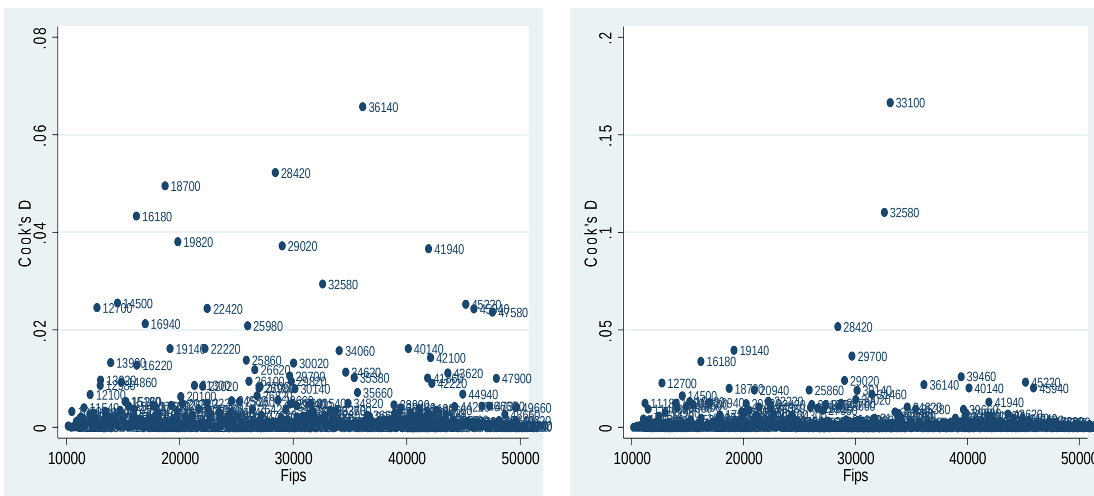
Models	Results	
	Moran I statistic	p-value
Model 1	0.1796	0.00
Model 2	0.1865	0.00

Table G.5 Results of the LM Test for Instability Models

Types of test statistics	Model 1		Model 2	
	Statistic	p-value	Statistic	p-value
LM error	35.94	0.00	38.77	0.00
LM lag	44.65	0.00	46.20	0.00
Robust LM error	0.01	0.91	0.07	0.79
Robust LM lag	8.72	0.00	7.50	0.01
Selected model type	Spatial lag model		Spatial lag model	

APPENDIX H. DIAGNOSTICS OF INFLUENTIAL OBSERVATIONS

In order to assess the changes in estimation with some extreme case, I applied Cook's D (Cook, 1977) for all regression models. Figure H.1 shows the scattering pattern of Cook's D for the both types – restricted and full – of growth models. The labeled numbers indicate the FIPS (Federal Information Processing Standard) codes for each MSA.



Restricted

Full

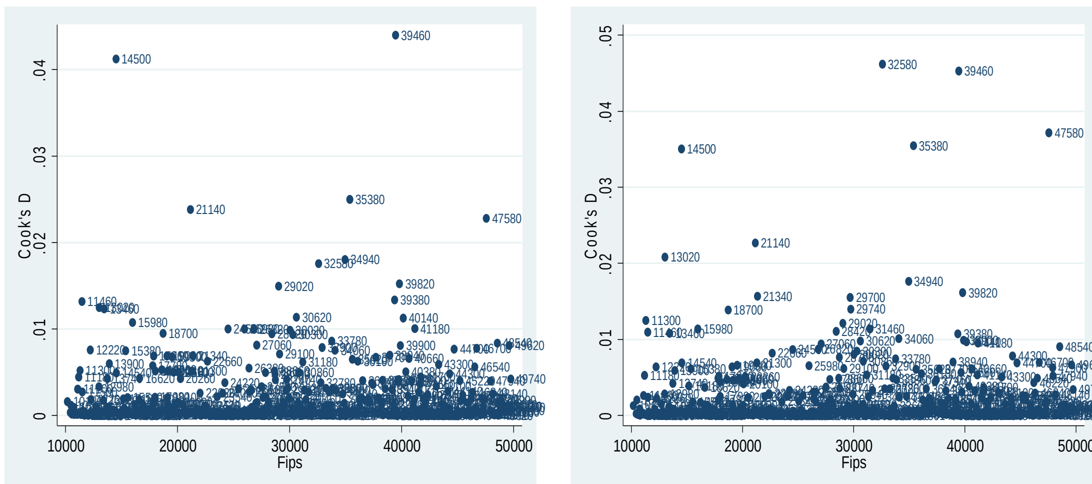
Figure H.1 Cook's D of the Growth Models (1998-2010)

As we can see the above figure, the metropolitan area (Ocean city, NJ) with the FIPS of 36140 indicates the extreme value of Cook's D. To see the effect of this influential case, I estimated the same growth model without this MSA. Similarly, I estimated the full growth model without two influential cases (Miami-Fort Lauderdale-Miami Beach, FL & McAllen-Edinburg-Pharr, TX) that were also detected by Cook's D. The estimation results of both growth models without the influential observations are reported in Table H.6. These results are substantially similar with the results reported in Table 6.3.

Table H.6 Regression Results of the Growth Models without Influential Cases

Variable	Model 1		Model 2	
	Coef	p-value	Coef	p-value
Intercept	0.818	0.612	0.998	0.433
Economic structure variable				
Diversity (*DIV*)	-1.018	0.020	-0.976	0.009
Multiple Specializations (*MSI*)	3.679	0.000	3.242	0.000
General control variable				
Competition (*COMP*)	0.993	0.005	0.483	0.044
Education (*EDUC*)	0.021	0.004	0.022	0.000
Log Population Size (*POP*)	0.010	0.852	-0.007	0.858
Geographical dummies				
Midwest region (*MW*)	-0.397	0.020	-0.203	0.108
Northeast region (*NE*)	0.154	0.378	0.355	0.007
South region (*S*)	0.072	0.593	0.253	0.015
Performance of Individual sectors				
Manufacturing (*MANU*)			0.143	0.000
Education and health services (*EDH*)			0.202	0.000
Past performance				
Past_5year_growth (*Past_EG*)	0.310	0.000	0.211	0.000
Past_5year_instability (*Past_INSTAB*)	0.093	0.422	-0.020	0.815
R-squared	0.451		0.634	
Adjusted R-squared	0.434		0.621	
Number of Observations	352		351	

For the instability models, I conducted the same steps. As can see Figure H.2, the two metropolitan areas – Punta Gorda, FL (39460) and Boulder, CO (14500) – were detected as influential cases for the restricted instability model.



Restricted Full

Figure H.2 Cook's D of the Instability Models (1998-2010)

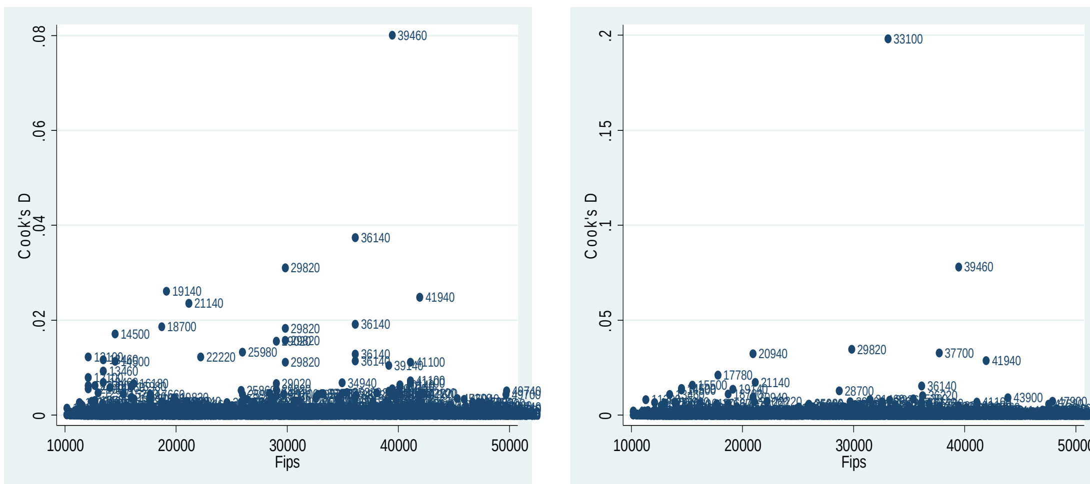
For the full instability models, five cases – McAllen-Edinburg-Pharr, TX ; Punta Gorda, FL; Boulder, CO; New Orleans-Metairie-Kenner, LA; Warner Robins, GA – were detected (Figure H.4).

To see the effect of this influential case, I estimated the same instability models without these influential cases. The estimation results are reported in Table H.7. These results are substantially similar with the results reported in Table 6.5.

Table H.7 Regression Results of the Instability Models without Influential Cases

Variable	Model 1		Model 2	
	Coef	p-value	Coef	p-value
Intercept	-3.149	0.000	-3.045	0.000
Economic structure variable				
Diversity (*DIV*)	-0.350	0.027	-0.336	0.028
Multiple Specializations (*MSI*)	-1.140	0.001	-1.112	0.000
General control variable				
Competition (*COMP*)	0.500	0.000	0.472	0.000
Education (*EDUC*)	-0.011	0.000	-0.010	0.000
Log Population Size (*POP*)	0.096	0.000	0.085	0.000
Geographical dummies				
Midwest region (*MW*)	-0.147	0.016	-0.128	0.037
Northeast region (*NE*)	-0.248	0.000	-0.226	0.000
South region (*S*)	-0.101	0.068	-0.099	0.074
Performance of Individual sectors				
Manufacturing (*MANU*)			-0.004	0.634
Education and health services (*EDH*)			0.030	0.059
Past performance				
Past_5year_growth (*Past_EG*)	0.110	0.000	0.099	0.000
Past_5year_instability (*Past_INSTAB*)	0.109	0.008	0.130	0.001
R-squared	0.403		0.427	
Adjusted R-squared	0.386		0.407	
Number of Observations	351		348	

I applied the same steps for the diagnostics of influential cases in the panel models. Because the Random effects model itself does not automatically produce the values of Cook's D in STATA, I detected the influential cases for the panel model based on the results by pooled OLS regression. As depicted in Figure H.3, Punta Gorda, FL was detected as an influential case for the restricted growth panel model. In addition, this figure also shows the influential cases – Punta Gorda, FL and Miami-Fort Lauderdale-Miami Beach, FL – for the full growth panel model.



Restricted   Full

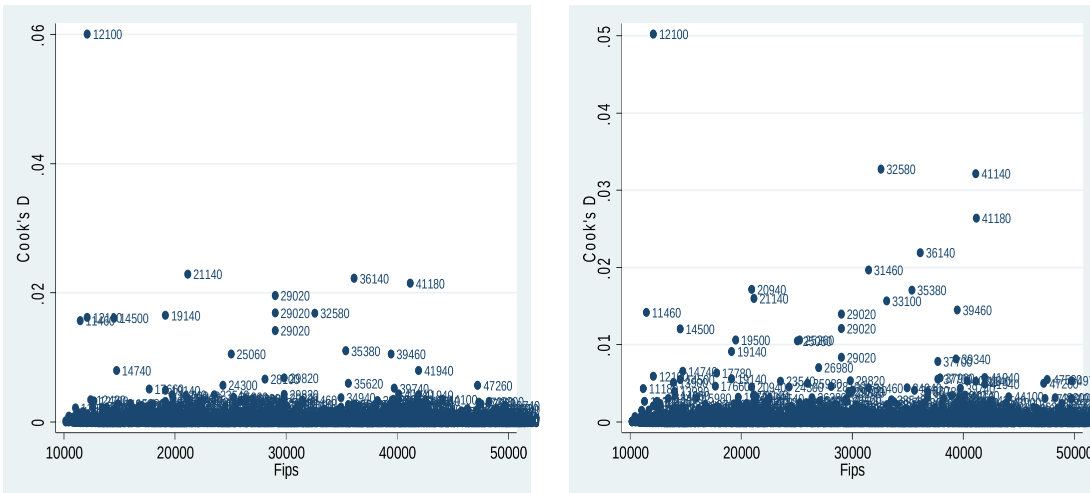
Figure H.3 Cook's D of the Growth Panel Models

Table H.8 shows the results of growth panel models without influential cases. The results reported in Table H.8 are also similar with the results in Table 6.9.

Table H.8 Regression Results for the Growth Panel Models without Influential Cases

Variable	Model 1				Model 2			
	Pooled OLS		Random effects		Pooled OLS		Random effects	
	Coef	p-value	Coef	p-value	Coef	p-value	Ceof	p-value
Intercept	-3.640	0.000	-3.339	0.002	-3.189	0.000	-3.051	0.000
Macroeconomic condition dummy								
Economic boom periods (*BOOM*)	3.790	0.000	3.937	0.000	2.456	0.000	2.501	0.000
Economic structure variable								
Diversity (*DIV*)	-2.076	0.001	-1.945	0.003	-1.868	0.000	-1.807	0.000
Multiple Specializations (*MSI*)	5.109	0.000	4.750	0.000	3.846	0.000	3.724	0.000
Interaction terms: Economic structure variable*BOOM / Competition*BOOM								
*DIV*BOOM*	1.506	0.062	1.526	0.044	1.454	0.013	1.457	0.010
*MSI*BOOM*	-4.909	0.005	-5.230	0.001	-3.831	0.002	-3.934	0.001
*COMP*BOOM*	0.672	0.163	0.642	0.157	0.083	0.813	0.080	0.814
General control variable								
Competition (*COMP*)	0.353	0.362	0.424	0.321	0.525	0.063	0.522	0.075
Education (*EDUC*)	0.018	0.002	0.008	0.285	0.025	0.000	0.024	0.000
Log Population Size (*POP*)	0.030	0.531	0.032	0.592	0.056	0.119	0.052	0.182
Geographical dummies								
Midwest region (*MW*)	-0.783	0.000	-0.795	0.000	-0.426	0.000	-0.445	0.000
Northeast region (*NE*)	-0.520	0.000	-0.511	0.005	-0.272	0.013	-0.287	0.016
South region (*S*)	-0.198	0.105	-0.228	0.129	0.026	0.768	0.015	0.879
Performance of Individual sectors								
Natural Resources and Mining (*NRM*)					0.000	0.818	0.000	0.801
Construction (*CONS*)					0.123	0.000	0.123	0.000
Manufacturing (*MANU*)					0.102	0.000	0.101	0.000
Information (*INFO*)					0.027	0.000	0.027	0.000
Education and Health Services (*EDH*)					0.069	0.000	0.063	0.000
Overall R-squared	0.4601		0.4589		0.720		0.720	
Number of Observations	1408				1402			

Otherwise, as depicted in Figures H.4, Atlantic City, NJ was detected as an influential case for both types – restricted and full – of instability panel models.



Restricted Full

Figure H.4 Cook's D of the Instability Panel Models

Table H.9 shows the results of instability panel models without influential cases. The results reported in Table H.9 are substantially similar with the results in Table 6.12.

Table H.9 Regression Results for the Instability Panel Models without Influential Cases

Variable	Model 1				Model 2			
	Pooled OLS		Random effects		Pooled OLS		Random effects	
	Coef	p-value	Coef	p-value	Coef	p-value	Ceof	p-value
Intercept	-3.646	0.000	-3.805	0.000	-3.738	0.000	-3.898	0.000
Macroeconomic condition dummy								
Economic boom periods (*BOOM*)	-0.722	0.000	-0.738	0.000	-0.602	0.001	-0.603	0.000
Economic structure variable								
Diversity (*DIV*)	-0.460	0.016	-0.411	0.044	-0.477	0.010	-0.444	0.026
Multiple Specializations (*MSI*)	-1.243	0.001	-1.149	0.003	-1.130	0.002	-1.034	0.007
Interaction terms: Economic structure variable*BOOM / Competition*BOOM								
*DIV*BOOM*	-0.706	0.005	-0.767	0.001	-0.742	0.003	-0.793	0.001
*MSI*BOOM*	0.711	0.170	0.810	0.095	0.660	0.192	0.737	0.119
*COMP*BOOM*	0.123	0.398	0.104	0.439	0.176	0.218	0.150	0.255
General control variable								
Competition (*COMP*)	0.320	0.006	0.365	0.004	0.306	0.007	0.362	0.004
Education (*EDUC*)	-0.006	0.001	-0.003	0.170	-0.007	0.000	-0.005	0.027
Log Population Size (*POP*)	-0.054	0.000	-0.055	0.002	-0.055	0.000	-0.054	0.002
Geographical dummies								
Midwest region (*MW*)	-0.065	0.123	-0.050	0.338	-0.093	0.026	-0.079	0.120
Northeast region (*NE*)	-0.269	0.000	-0.269	0.000	-0.285	0.000	-0.286	0.000
South region (*S*)	0.022	0.552	0.040	0.369	0.009	0.808	0.023	0.598
Share of Individual sectors								
Natural Resources and Mining (*NRM*)					0.000	0.397	0.000	0.391
Construction (*CONS*)					-0.012	0.000	-0.012	0.000
Manufacturing (*MANU*)					-0.009	0.001	-0.010	0.000
Information (*INFO*)					-0.005	0.001	-0.005	0.000
Education and Health Services (*EDH*)					-0.001	0.897	-0.002	0.591
Overall R-squared	0.2802		0.2780		0.3186		0.3172	
Number of Observations	1408							