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Will Specialization Continue Forever? A Case Study of Interactions between Industry Specialization and Diversity

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ABSTRACT

This paper studies the interactions between industry specialization and diversity. Several studies have shown that competitive industries in a region grew faster, thus expanding their shares in overall employment. The implication is that a region will become more specialized in its competitive industries and the process will continue forever baring external intervention. Utilizing an econometric model on county level employment growth in Virginia, this study confirms that competitive industries experience faster employment growth, reinforcing specialization. However, as specialization proceeds, it reduces economic diversity. That will hurt job creation, as economic diversity also stimulates employment growth. The interactions between specialization and diversity can lead to complex patterns of industry structural change. This study concludes that if a locality starts with low economic diversity, specialization will continue to deepen and the region may be trapped with limited economic diversity. However, when an economy starts with high diversity, specialization and diversity tend to offset each other, resulting a more consistent industry structure. (JEL Code R1)

Keywords: specialization; industrial diversity; externality; cluster

1. Introduction

In the debates among economists on regional economic development, there are two views regarding the optimal strategy to promote sustained employment growth. Should a region's economic development effort be focused on specializing in a few key industries or on diversifying a region's industry base? Since Porter (1990) popularized the idea of industry cluster, many localities have pursued a development strategy centering on cluster building, based on the belief that companies in same industries are likely to be close to each other to share their suppliers and customers (Krugman, 1991), as well to share knowledge and know-hows (Romer, 1986). However, other studies pointed to the danger of this strategy, and argued that a diverse local economy was better for sustained economic growth, since economic diversity helped knowledge spillover across industries (Jacobs, 1969), and enabled local economy avoiding downturns when technology and economic conditions change (Diets and Garcia, 2002).

The theoretical foundation of this debate can be found in the externality theories in economic growth. Two types of externality are often studied. The Marshall-Arrow-Romer (MAR) externality refers to knowledge spillover among firms within an industry. Arrow (1962) provided an early formalization of this externality and Romer's (1986) endogenous growth model linked this externality to economic growth. MAR externality indicates that knowledge and technology can spread faster as workers move easily among close-knit firms within a concentrated industry. As a result, the clustering of similar companies in a location can improve their productivity and stimulate expansion. However, Jacobs (1969) believed that the most important knowledge spillover came from outside an industry. As a result, the diversity of geographically close-knit industries, rather than clustering of similar firms, promotes innovation and growth. This knowledge spillover across industries is called Jacobs externality. Both theories have empirical supports. While several empirical studies concluded that competitive industries grew faster (Forni and Paba, 2002), and generated more new businesses and start-ups (Rosenthal and Strange, 2003), Glaeser, *et. al.* (1992) found that industry diversity, rather than specialization, stimulated industry level employment growth. In addition, other studies (Henderson *et. al.* 1995) found evidence of both MAR and Jacobs externalities in manufacturing industries.

Many previous empirical studies reached "either/or" conclusions regarding the roles of MAR and Jacobs externalities in economic growth. Their conclusions accepted the presence of either one externality or the other. Even for those studies that found evidence of both externalities (Henderson *et. al.*, 1995), they did not consider the possibility that industry specialization and diversity are interrelated. As a region builds up agglomeration in one industry, one unintentional effect is that its economy becomes less diversified. As a result, if economic diversity is important to economic growth, one should not ignore the negative effect of reduced diversity as specialization proceeds. In that sense, specialization has a secondary effect on growth through its influence on economic diversity.

The interactions between MAR and Jacobs externalities are important in shaping a region's industry structure. If only MAR externality exists, a competitive industry should grow faster than other industries in a region. As a result, its share in total employment will expand, accelerating its future growth. The logic end result will be that different regions will specialize solely in their competitive industries, as predicted by the theoretical model developed by Krugman (1991). On the other hand, if only Jacobs externality exists, a competitive industry may grow slower and a regional economy will become less specialized and more diversified. Policy wise, the interplay of two externalities raises the questions of whether building industry clusters is a good development strategy.

This paper analyzes how MAR and Jacobs externalities affect each other and their roles in shaping the industry structure of a region. To achieve that goal, this study first derives the theoretical foundation where MAR affects Jacobs externality, based on a simple employment growth model. This study then builds an econometric model of employment growth in Virginia to determine both the existence and the magnitude of two externalities. Utilizing parameters estimated by the econometric model, this study then analyzes the conditions under which specialization can promote or hinter economic growth. This paper attempts to fill the gaps of the current empirical literature where the interactions between two externalities are not completely explored.

Following the introduction, Section 2 defines the key concepts of industry specialization and diversity. It also lays out the analytical framework to study the interactions between these two externalities. Section 3 specifies the econometric model and discusses the regression results, based on the industry employment growth data of Virginia's cities and counties. Section 4 analyzes how industry specialization and diversity interact with each other in determining industry structure of a region, as well as policy implications. Section 5 offers a conclusion and areas for future research.

2. Analytical Framework

2.1. Measurements of MAR and Jacobs Externality

In this study, MAR externality is represented by industry specialization as a large number of workers in an industry imply a high level of knowledge spillover. The industry specialization is measured by Location Quotient (*LQ*), widely used to define industrial agglomeration and competitiveness of a region's industry (Glaeser *et. al.,* 1992; Hanink, 2006). The location quotient measures the degree to which an industry is concentrated in a region relative to that of the nation, by computing the ratio of the share of industry *i*'s employment in region *j* to the same industry's share of employment in the nation. A locality with a high location quotient in an industry is considered to be competitive, or specialized in this industry.

Let subscript *i* indicate industry and *j* indicate location, the location quotient can be computed with the following formula:

$$LQ_{ij} = \frac{Emp_{ij} \big/ Emp_{j}}{Emp\_National_{i} \big/ Emp\_National} \qquad (2)$$

Jacobs externality is represented by economic diversity. Over the years, there have been several proposed measurements of economic diversity. Wagner (2000) compared and contrasted those indexes. Industry diversity measures are commonly calculated based on certain standards. For some indexes, such as Ogive, Herfindalh, and Dixit-Stiglitz indexes, the standard is the equal-proportional levels of all industries. For these three indexes. the highest degree of diversity is achieved when each industry has an equal share in total employment (Wagner, 2000). Other diversity indexes, such as national average index, Hachman index (1995), as well as input-output index proposed by Wagner-Deller (1998), used national economic structure as the standard, assuming national economy is completely diversified. For those indexes, the highest level of economic diversity is achieved when the regional industry structure is the exactly same as the national one. [1]

The diversity measured based on equal-proportional index has been questioned both theoretically and empirically. The idea of an equal distribution of economic activities across sectors is not based on any economic theory, and was arbitrary (Wagner, 2000). Empirically, some of the highly specialized regions defined by equal-proportional indexes were characterized by relative economic stability, contrary to the hypothesis that economic diversity foster growth and stability (Wagner and Deller, 1998).

Diversity measures using national industry structure as a standard takes into account the consumer demand. A diversified economy should produce various products or services to satisfy consumer needs. Due to differences in productivity and labor requirements, an industry structure meeting consumer demands may not result in equal employment for all industries. Despite large trade deficit in the United States, the national economy is still better equipped to meet the consumer demand than state and local economies. Therefore, using national economy

[1] See Appendix 3 for a detailed discussion on the formula, calculation, and the effect of various diversity indexes on location-industry employment growth.

as a benchmark is more theoretically sound. As a result, this study uses one of the diversity indexes with national economic structure as a standard.

Among the possible diversity indexes using national industry structure as benchmark, Hachman diversity index was utilized in this study as a measure of Jacobs externality. Compared with national average or input-output indexes proposed by Wagner and Deller (1998), Hachman index utilizes LQ in its calculation, providing a direct link between two externalities.[2] This also makes the theoretical analysis of the interaction between two externalities easier to derive analytically.

As a result, the diversity index (*DI*) in this study is calculated as the inverse of the sum of the weighted location quotients of all industries in a locality (Hachman, 1995 and Diets and Garcia, 2002). The more similar of a location's industry mix is to the national industry mix, the higher the diversity index will be. If a region's employment distribution in different industries is the same as the national distribution, the diversity index is 100%, the maximum possible value.

Let *i* indicate industry and *j* denote locality, the diversity index can be expressed as:

$$DI_j = \frac{1}{\sum_i LQ_{ij} * \frac{Emp_{ij}}{Emp_j}} \tag{3}$$

2.2. Analytical Model

The analytical framework of this study follows a model developed by Glaser *et. al* (1992). They treated the technology advance of an industry as a function of industry specialization and diversity, representing MAR and Jacobs externalities respectively. Let A_{ij} be the technology level of industry *i* and location *j*, and $log(A_{ij}^{t+1} / A_{ij}^{t})$ represents the growth rate of technology level from time *t* to time *t+1:*

[2] Appendix 3 shows that using national average index can produce similar results in econometric estimation. Data for computing input/output based diversity index are too costly to obtain.

$$\log\left(\frac{A_{ij}^{\,t+1}}{A_{ij}^{\,t}}\right) = F(LQ_{ij}^{\,t}, DI_j^{\,t}, Initial\_conditions) \tag{4}$$

Profit maximization dictates that firms set their employment levels (*Emp*) as a function of equilibrium wages and technological level. As a result, the employment growth rate of an industry (EG_{ij}) can be written as:

$$EG_{ij}^{\,t+1} = \log\left(\frac{Emp_{ij}^{\,t+1}}{Emp_{ij}^{\,t}}\right) = -\log\left(\frac{Wage_{ij}^{\,t+1}}{Wage_{ij}^{\,t}}\right) + F(LQ_{ij}^{\,t}, DI_j^{\,t}, Initial\_conditions) \tag{5}$$

This model associates industry level employment growth of a locality with MAR and Jacobs externalities. If MAR externality exists, we will have $\frac{\partial F}{\partial LQ_{ij}} > 0$, or $\frac{\partial EG_{ij}}{\partial LQ_{ij}} > 0$. If Jacobs externality exists, we will have $\frac{\partial F}{\partial DI_j} > 0$, or $\frac{\partial EG_{ij}}{\partial DI_j} > 0$.

However, the specialization and diversity are related. As a regional economy becomes more specialized, its economy inevitably becomes less diverse. More precisely, using the specialization and diversity measures defined in (2) and (3), an increase in the specialization of industry *i* can reduce the diversity index of locality *j*:

$$\frac{dDI_j}{dLQ_{ij}} = -DI_j^2 * \frac{Emp_{ij}}{Emp_j} \tag{6}$$

As a result, the effect of specialization on industry employment growth, accounting for changes in diversity index, can be written as:

$$\frac{dEG_{ij}}{dLQ_{ij}} = \frac{\partial EG_{ij}}{\partial LQ_{ij}} - \frac{\partial EG_{ij}}{\partial DI_j} * DI_j^2 * \frac{Emp_{ij}}{Emp_j} \tag{7}$$

Depending on which externality exists, there are four possible patterns of interaction between MAR and Jacobs externalities, leading to different outcomes of the regional industry structure (See Table 1).

Table 1: Interaction Patterns of MAR and Jacobs Externalities

Patten	MAR Externality	Jacob Externality	Potential Results (Other factors equal)
1	0	0	Stay in initial structure
2	+	0	Continuous Specialization
3	0	+	Approach Perfect Diversity
4	+	+	Effect offset each other, depending on parameters

If none of MAR or Jacobs externality exists, there will be no knowledge spillover within or across industries. Based on Equation (7), industry specialization and diversity will have zero effect on industry level employment growth. Consequently, the job growth of a location will depend on other economic factors such as population, infrastructure, human capital, and business costs (Carlino and Mills, 1987).

In the case where only MAR externality, but no Jacobs externality, exists, there will be knowledge spillover within similar industries. The industries with initial agglomeration will benefit more from this spillover and their employments will grow faster than other industries. As a result, their shares in total employment will expand. Other factors equal, MAR externality will drive this process continuously to approach complete specialization, where each location specializes in its initially competitive industry.

In the case where only Jacobs externality, but no MAR externality, exists, the opposite will occur. Industry agglomeration will have a negative effect on industry employment growth as it reduces economic diversity and limits knowledge spillover across industries. The consequence is that initially competitive industries will grow slower, resulting declining shares in total employment. This process will continue until local industry structure approaches complete diversification, which means that local industry structure will resemble that of the nation, when using diversity definition of Equation (2). Under that scenario, the diversity index of each location approaches 100%, and the location quotient for each industry approaches 1. Other things equal, the employment of each industry will grow at the same rate thereafter.

The fourth pattern is that both MAR and Jacobs externalities exist. Under that scenario, both specialization and diversity can stimulate growth, and the effect of two externalities will offset each other. That is because as specialization deepens, an economy becomes less diverse. According to Equation (7), the net effect of specialization on industry employment growth will depend on two key parameters—the current diversity index of a location and the current employment share of an industry.

Equation (7) suggests that the stimulating effect of specialization diminishes with the industry diversity of a location. That is because in a highly diverse economy, strong Jacobs externality exists. A same level of increase in specialization will reduce economic diversity more severely in highly diverse economies than in ones with low diversity. In a less diverse economy, since there is no strong positive inter-industry spillover to begin with, the economy will benefit less from industry diversity. The implication is that the effect of MAR externality is more pronounced in a less diverse economy.

Equation (7) also indicates that the stimulating effect of industry specialization declines with its current employment share. The reason is that *DI* is weighted by employment. So, a change in location quotient for a big industry will reduce regional diversity more than small industry. This implies that MAR externality is more important for small or emerging industries. As industries mature and grow in importance, the negative effect of reduced diversity becomes more influential.

Equation (7) only represents the effect of specialization of industry *i* on its own employment growth (EG_{ij}). Since the diversity measure could impact all other regional industries, increased specialization of industry *i* would also affect the overall employment growth of location *j* (EG_j). This effect is represented by:

$$\frac{dEG_j}{dLQ_{ij}} = \frac{Emp_{ij}}{Emp_j} * \frac{\partial EG_{ij}}{\partial LQ_{ij}} - DI_j^2 \frac{\partial EG_{ij}}{\partial DI_j} \tag{8}$$

Equation (8) suggests that the effect of increased specialization on overall employment growth increases with its employment share and decreases with the diversity index of a location.

3. Empirical Effect of Specialization and Diversity

The rest of this paper will use industry employment data from Virginia to determine which of the four patterns in Table 1 fits the actual data, and how those two externalities affect each other in driving industry structure of a region. It first uses a simple econometric model to quantify the effect of industry specialization and diversity on employment growth. Using estimated coefficients in the analytical model, it then analyzes whether and how that can affect the growth path of Virginia.

3.1. Industry Specialization and Diversity in Virginia

There are 134 counties and cities in Virginia. Based on Northern American Industry Classification System (NAICS), all industries in a locality are classified into 11 major industry sectors in this study. Those are (1) agriculture, mining and natural resource, (2) construction, (3) manufacturing, (4) trade, transportation and utility, (5) information, (6) financial service, (7) professional and business service, (8) education and health service, (9) leisure and hospitality, (10) other service, and (11) public administration.[3]

Due to Virginia's diverse geographical environments and natural resources, the state's counties and cities are competitive in different industries. For example, Northern Virginia is a national center for high-tech and information technology industries. Hampton Roads area in southeast Virginia has a concentration in shipbuilding and other defense related industries. Additionally, southwest Virginia has a strong mining base and central Virginia is competitive in finance and government sectors. This diversified economic base provides an ideal case to study the interactions between industry competitiveness and diversity at local level.

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[3] Ideally, a more detailed industry, such as industries at the 3- or 4-digit NAICS level should be used to better capture the inter-industry spillover. However, the publicly available county level industry employment data, released by Virginia Employment Commission, are only available at the major NAICS sector level. Please follow the following link for an explanation. http://www.vawc.virginia.gov/analyzer/session/session.asp?CAT=HST_EMP_WAGE_IND

For economic diversity in Virginia, highly diverse local economies seem to be clustered around the three largest metropolitan areas of the state, namely Northern Virginia, Central Virginia around Richmond, and Hampton Roads region in southeast Virginia. The least diversified counties are southwest Virginia mining counties, and southern Virginia counties that rely heavily on tobacco farming and textile manufacturing.

3.2. Econometric Model

According to the theoretical model developed by Glaeser *et. al.* (1992), the employment growth of a region's industry is a function of industry specialization, diversity, and initial conditions, as specified in Equation (5). Naturally, the measures of specialization and diversity, as defined in Equation (2) and (3), are included in the empirical model. For initial conditions, two measures—initial wage level and initial employment size of an industry—are consistently used in many studies of industry growth (Glaeser *et. al.*, 1992; Henderson *et. al.*, 1995). Since firms tend to move to low wage areas, regions with low wages are likely to have faster employment growth. Including initial wages accounts for those effects. Similarly, high initial employment reduces employment growth, an empirical fact that has been observed by several studies (Glaeser, *et. al*, 1992; Wheeler, 2006).

Other initial conditions used as control variables are related to location specific factors. Several empirical studies (Carlino and Mills, 1987; Hanink, 2006) have shown that location specific variables, such as population, cost of living, education attainment, tax, and infrastructure, have empirical significance in county level employment growth. Though this study focuses on the effect of industry specialization and diversity, an extensive list of location specific variables are included as control variables. Let *i* denote industry and *j* denote locality, this study utilizes the following model specification:

$$EG_{ij} = \beta_0 + \beta_1 LQ_{ij} + \beta_2 DI_j + \beta_3 Emp_{ij} + \beta_4 Wage_{ij} + \sum_k \phi_k X_k + \mu_{ij} \quad (9)$$

In Equation (9), LQ_{ij} and DI_j are primary variables of interest. X_k is a list of location specific variables measuring initial social economic conditions. For a detailed description of dependent and independent variables, please see Appendix 1.

In a cross-sectional model, heteroskedasticity is a major concern, which needs to be accounted for in model specification. In addition to random errors (white noises), there are two types of systematic variations contributing to possible heteroskedasticity. One type is unobserved industry variation, while the other is unobserved location variation. The error structure can be written as:

$$\mu_{ij} = \varepsilon_i + \lambda_j + \eta_{ij} \tag{10}$$

In Equation (10), η_{ij} is white noise, ε_i represents industry variation and λ_j represents location variation. Since several location specific factors, such as population, tax, and education level are already included in the model, they will account for a large portion of location variation. The remaining location variation is limited. As an extra caution, this model experiments with including location dummy variables for the three largest metropolitan statistical areas in Virginia—Northern Virginia, Hampton Roads, and Richmond, aiming to account for unobserved location variation that is not captured by explicitly modeled location variables. For unobserved industry difference (ε_i), though industry dummy variables can be used to capture them, this model utilizes random effects technique to account for those differences. These two treatments effectively eliminate the heteroskedascity. The final empirical model can be written as:

$$\begin{aligned} EG_{ij} &= \beta_0 + \beta_1 LQ_{ij} + \beta_2 DI_j + \beta_3 Emp_{ij} + \beta_4 Wage_{ij} + \sum_k \phi_k X_k + \\ &\sum Location\_Dummy + \sum Industry\_Random\_Effect + \eta_{ij} \end{aligned} \tag{11}$$

There is no simultaneity issue in this model specification. The dependent variable (EG_{ij}) measures the employment growth from 1990 to 2003. All independent variables are based on 1990 values, including population, industry employment, wage level, location quotient, and diversity index. None of those independent variables are determined after 1990.

Despite controlling for location variances, since the contiguous counties are utilized in econometric analysis, the spatial correlation for the error terms (was also tested. For the finalized model specification, the Moran's I is --0.0002, with a P value of 0.21. This test fails reject the null hypothesis that there is no spatial autocorrelation in the model chosen. [4]

3.3. Empirical Effect of Industry Specialization & Diversity

There are 134 localities in Virginia. If each of them has 11 industry sectors, the dataset will have 1474 records. However, the sample is not balanced and a few industries are missing in some localities. While some cities do not have agricultural and mining industry, several small rural counties do not have information industries. As a result, the total sample size is 1,431. Appendix 1 lists descriptive statistics of all variables in this model.

Coefficient estimates are listed in Appendix 2. Different combinations of location dummy variables and social economic factors are experimented to ensure that the coefficient estimates of key variables are robust. The coefficient estimates for two key variables (*LQ* and *DI*) are consistent across 7 model specifications. For *LQ* variable, all seven models yield coefficient estimate of either 0.02 or 0.03. All of them are significant at 95% level. As a result, the estimates for *LQ* are robust. For *DI* variable, the coefficient estimates for seven models vary from 0.20 to 0.31, with 5 of them significant. Even the non-significant ones have correct signs. Though the coefficient estimates of this variable are less robust than that of LQ, they are still acceptable. This study uses coefficient estimates in model 1 to study the interactions between industry specialization and diversity, as this model specification exhibit no spatial auto-correlation in its error terms. For a description of the coefficient estimates of other variables, please see Appendix 2.

The empirical model shows that the past industry competitiveness has a strong impact on industry employment growth. The coefficient estimate is positive (0.03) and significant at 95%

[4] Some of other model specifications show some degree of spatial auto-correlation. The coefficients estimate from those model specifications are not used in further analysis.

level, supporting MAR externality theory. This result is similar with previous empirical studies by Henderson, *et. al.* (1995) and Foni and Papa (2002), and contrary to the finding by Glaeser *et. al.* (1992). MAR externality theory claims that in specialized industries where a large number of similar firms are concentrated, due to knowledge sharing and economy of scale, they tend to have a higher rate of technological advance. That gives industries a competitive advantage to expand faster than similar industries elsewhere. In addition, empirical studies (Wu, 2000; Rosenthal and Strange, 2003) have shown that start-up or expanding firms tend to locate in the areas where agglomeration has occurred. These two effects contribute to the faster job growth in competitive industries.

The model shows that industry diversity also has a strong and positive effect on industry employment growth, with a coefficient estimate of 0.20, significant at 90% level. This result is consistent with the findings by Glaser *et. al.* (1992), supporting the Jacobs externality theory that economic diversity can stimulate economic growth. Economic diversity can increases knowledge spillover across industries and helps the region avoid the economic risks (Dietz and Garcia, 2002).

It needs to be noted that the presence of both externalities may explain the result that Glaeser *et. al.* (1992) did not find a positive growth effect of agglomeration. Their studies included only the top 5 industries in each city. As Equation (7) shows, one key implication of the interactions between specialization and diversity is that the stimulating effect of specialization diminishes as an industry grows in importance. This positive effect is more pronounced in emerging industries, less so in mature industries. As a result, the choice of top 5 industries by Glaeser *et. al.* (1992) may lead to no findings of positive effect due to the offsetting effects of economic diversity on specialization.

The regression results find evidence of both MAR and Jacobs externalities, which suggests that the employment growth in Virginia follows the Pattern 4 in Table 1. As a result, the industry structure in Virginia's localities may not approach a complete specialization or perfect diversity. Rather, the growth rates of different industries will depend on the interactions between two externalities, as will be detailed in the remainder of this paper.

4. Interactions between Specialization and Diversity in Virginia

4.1. The Effect of Interaction on Industry Employment Growth

The job growth experience of Virginia's cities and counties provides evidence supporting both MAR and Jacobs externalities. Due to the interactions between them, the stimulating effect of MAR is reduced by Jacobs externality. According to Equation (9), the effect of specialization on industry employment growth can be written as:

$$\frac{dEG_{ij}}{dLQ_{ij}} = \beta_1 - \beta_2 DI_j^2 \frac{Emp_{ij}}{Emp_j} \tag{12}$$

Since the estimates of both β_1 and β_2 are positive, the net effect of specialization on industry employment growth is not necessarily positive. The effect is positive only when an industry's employment share is less than the critical value of $\frac{\beta_1}{\beta_2 DI_j^2}$. For any industries whose initial employment shares are greater than that critical value, increased specialization will slow down industry employment growth.

Equation (12) indicates that the stimulating effect of the specialization of an industry declines as its employment share increases. The implication is that small and emerging industries benefit more from agglomeration than big and mature ones. For emerging industries, since technologies for those industries are still in the development stage, specialized knowledge and skills are essential for their success. As a result, clustering of the similar firms can help the diffusion of specialized knowledge and technology, and stimulate faster growth. As for mature industries, since their own technologies are well developed, new innovations and ideas are more likely to come from other industries. As a result, they will benefit more from economic diversity, and less from increased agglomeration.

FIGURE 1 Here

The critical value of $\frac{\beta_1}{\beta_2 DI_j^2}$ decreases with diversity index, as illustrated in Figure 1. The shaded region represents employment shares of the industries whose agglomeration will stimulate industry employment growth. As diversity index increases, the critical value decreases. For example, when the diversity index is 70%, the critical value is 30%. When diversity index is 100%, the critical value is reduced to 15%. On the other hand, when diversity index is less than 36%, the critical value is 1. That implies agglomeration of any industries can lead to faster employment growth.

In Virginia's cities and counties, with up to 11 industry sectors in each locality, the critical value seems to be high for many localities, and a lot of industries are in the shaded region in Figure 1. There are only limited cases where the employment share of an industry is over the critical value, resulting in negative growth effect of agglomeration. In all 1431 location-industries, only 45 location-industries, or 4% of the total, had employment shares greater than the critical value. For those 4% industries, industry specialization reduces jobs growth. For the rest of industry sectors, industry agglomeration can still stimulate industry employment, even accounting for reduced diversity.

The implication is that even though both MAR and Jacobs externalities exist, continuous specialization is still possible for most industries, especially for those industries with smaller employment shares, and/or in locations with modest economic diversity. When initial diversity index is small, competitive industries grow faster, pushing specialization further. As specialization deepens, the diversity index becomes smaller, resulting a larger critical value. That in turn makes industries less likely to grow over the critical value. When a region's diversity index is 36%, the critical value is 100%. That means if a county starts with a diversity index less than 36%, the employment share can never be big enough to reverse the trend of continuous specialization. As a result, its economy is trapped in its initially specialized state. In Virginia, 7 counties had diversity index of less than 36% in 1990, for which specialization will continue forever baring any external interventions.

This process is different when localities start with a high economic diversity. Even though competitive industries may still grow faster initially, the growing employment share is possible to cross the critical value, which is small with a high diversity index. When employment share is over the critical value, the process will reverse itself. The job growth for competitive industries will be slower than other industries. As that occurs, the industry structure will become more diversified.

In this context, the initial diversity condition is very important. Without exogenous shocks, the localities will be put on divergent paths depending on the initial level of economic diversity. Some localities will be locked in the path of continuous specialization, while others will be able to diversify their economies, or will see limited changes in their industry structures.

4.2. The Effect of Interaction on Overall Employment Growth

The economic development officials are usually responsible for the overall employment growth of their localities, rather than that of a particular industry. They may consider the effects of specialization on overall job growth, which can be expressed as:

$$\frac{dEG_j}{dLQ_{ij}} = \frac{Emp_{ij}}{Emp_j}\beta_1 - \beta_2 * DI_j^2 \qquad (13)$$

For an industry's specialization to have a positive effect on the employment growth of a locality, its employment share needs to be greater than the critical value of $\frac{\beta_2 DI_j^2}{\beta_1}$. In terms of overall job growth, the negative effect of reduced diversity is fixed. As a result, industries with lager employment shares will generate larger positive effects on total employment growth. The reason lies in the fact that larger industries usually have more extensive linkages with other local industries. Increasing their agglomeration can bring more job opportunities for those local businesses.

The critical value increases with diversity index. Figure 2 shows that when the diversity index is greater than 39%, the critical value is 1. The implication is that the specialization of no industry can have positive effect on overall employment growth when DI is greater than 39%. However, when a location's diversity index is smaller, there is a range of area where the agglomeration of multiple industries can stimulate overall employment growth. For example, when a location's *DI* is 5%, the critical value is only 2%. The agglomerations of any industry with over 2% employment share will have a positive effect on the overall employment growth in that location.

FIGURE 2 Here

In Virginia, the average diversity index of all localities was 66% in 1990. As a result, only three counties can find industries whose agglomeration will stimulate overall employment growth. For example, in Buchanan County, where the diversity index was 5%, 10 of the 11 industries have employment share larger than the critical value. For most other localities, it is impossible for them to find industries with shares larger than the critical value. As a result, those localities need to understand that the strategy of building agglomeration of any industry will slow down overall employment growth.

4.3. Policy Implications-to Cluster or not?

The analysis of interactions between industry specialization and diversity indicates that although cluster building strategy has theoretical and empirical support, there is also evidence that industry diversity has a positive effect on employment growth. In terms of growth effect, industry diversity provides a counter balance to agglomeration as increased specialization reduces diversity. The result is that the evolution of the industry structure in a locality does not follow a simple path. For localities starting with a low economic diversity, specialization will continue to deepen. With this knowledge, how should economic development officials approach the questions of whether they should specialize or diversify? Is the clustering strategy work? The answer to that question will be determined largely by the initial diversity and the industry competitiveness of a region.

For a few counties with small diversity index (less than 36%), the positive effect of specialization dominates the negative effect of reduced diversity, and specialization will continue forever. However, as discussed earlier, those counties can find themselves trapped in their own specializations. Though building clusters can bring in faster growth in competitive industries, the perils of this strategy is that technological and demographic change can make those industries obsolete in the future. As a result, it can be risky for them to pursue a clustering strategy. Only external forces can change this continuous specialization process. The local government can change this situation by actively attracting companies in less competitive industries, thus altering the industry mix externally.

For localities with diversity index greater than 36%, but not very high, policy makers have to be mindful that building clusters around competitive industries may stimulate faster employment growth in that sector. However, focusing competitive industries can reduce its diversity index to smaller than 36%, where economy can switch to a path of continuous specialization. To avoid falling into that trap, officials can choose to develop less competitive industries rather than building clusters around competitive industries.

For high diversity locations, even though competitive industries can still grow faster for a lot of industries, there is a limit to this. When an industry's employment share is high, building clusters can easily push its shares to be over the critical value, reducing industry growth. However, if competitive industries are still small in overall employment, the localities can focus on these selected industries, especially for the technology driven new industries where specialized technology are essential for their successes. In that case, clustering strategy can work for small and emerging industries.

In summary, the clustering strategy is not for every industry and every location. It can promote growth of emerging industries in high diversity areas. But it is risky for low-diversity locations because this strategy may put them in specialization trap, and expose them to economic risks.

5. Conclusion

Using industry employment data from Virginia's cities and counties, this study investigates the interactions between industry specialization and diversity, and their effects on employment growth at the industry and regional level. This paper provides four insights that have not been widely discussed in the literature.

First, this study recognizes the links between industry specialization and diversity. Though many studies investigated whether MAR or Jacobs externality exists, they did not study the interactions between them—the fact that Jacobs externality can offset the positive effect of MAR externality. While competitive industry can grow faster than other industries, the stimulating effect of agglomeration is muted by reduced industry diversity. Another finding is that industry agglomeration is more beneficial for employment growth when industries are small, but the effect tends to turn negative as industries grow.

Second, the study recognizes that while specialization can stimulate the employment growth of one industry, the effect of diversity impacts all industries. As a result, there is trade off between the faster growth of one industry versus that of a region. To achieving both goals are difficult. The localities with low diversity may do so as they benefit more from industry agglomeration.

More importantly, the analysis of interactions shows that the evolution of industry structure is complex. The specialization will not continue forever for all localities, but shows a divergent path. If a locality starts very specialized, it is possible for them to be trapped in this specialized state. However, for areas with high initial diversity, negative effect due to reduced diversity can overtake the positive effect of agglomeration. Their economies will become more diversified as a result. If two effects are with similar magnitude, the industry structure will remain consistent over the years. It needs to be noted that other social economic variables can also influence employment growth, thus pushing industry structure in other directions. The effects of those variables are not the objective of this study.

Finally, from a policy stand point of view, clustering development strategy is not for everyone. Clustering strategy is the most effective when local government wants to promote growth for emerging industries in high diversity areas. This strategy is risky for low-diversity regions because it may trap them in their specialized states. Clustering strategy is not good for large and mature industries as agglomeration can slow down employment growth.

There are several areas where future research can be pursued. The choice of *LQ* and *DI* as measurements of MAR and Jacobs externality are made for the purpose of easy manipulation. Appendix 3 shows that coefficient estimates for diversity index can be sensitive to the diversity standard chosen. Diversity indexes using equal proportion employment as standard tend not to be significant, while diversity indexes using national industry structure as standard tend to show that high diversity promote employment growth. Future research can investigate how sensitive the policy implications are with respect to different measurements. Secondly, the econometric model uses a pooled dataset of all industries. It is possible that specialization and diversity interact in different manners depending on industry type. In that case, separate models for each industry needs to be estimated, which can result in different coefficient estimates of the effect of specialization and diversity. In addition, when more detailed industry level data are available, they can be used to better capture inter-industry spillovers.

Despite those limitations, the main findings of this study is that the MAR and Jacobs externality are interrelated, and their interactions drives complex dynamics of industry structural evolution. Though this case study utilizes coefficient estimates specifically for Virginia, the implications can be generalized to other geographic regions, as the interactions between specialization and diversity are present at all levels.

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Appendix 1: Data Source and Descriptive Statistics

The following variables are used in the empirical model:

Table A1: Variable Description of Equation (11)

EG_{ij}	Employment growth rate in industry *i* location j from 1990 to 2003
LQ_{ij}	1990 location quotient for location *j* and industry *i*
DI_{j}	1990 industry diversity index of location *j*
Emp_{ij}	1990 total employment in industry *i* and location *j* (Log Terms)
$Wage_{ij}$	1990 wage level for location *j* and industry *i* (Log Terms)
Pop_{j}	1990 total population in county *j* (Log Terms)
HS_{j}	1990 percentage population with high school degree in location *j*
$COLI_{j}$	1990 Cost of Living Index for location *j* (log terms)
AP_{j}	Distance from center of location j to nearest commercial airport (log terms)
Tax_{j}	Real estate Tax rate of locality j
Industry Random Effect Variables	
AG	Random Effect for Agriculture, Natural Resource, and Mining Industry
CON	Random Effect for Construction Industry
MAN	Random Effect for Manufacturing Industry
TTU	Random Effect for Trade, Transportation and Utility Industry
INFO	Random Effect for Information Industry
FIN	Random Effect for Finance related Industry
PBS	Random Effect for Professional and Business Service Industry
EHS	Random Effect for Education and Health Industry
LH	Random Effect for Leisure Industry
OSERV	Random Effect for Other Services Industry

PUB	Random Effect for Pubic Administration
Location Dummy Variables	
NV	Dummy Variable for localities in Northern Virginia MSA
RIC	Dummy Variables for localities in Richmond MSA
HR	Dummy Variables for localities in Hampton Roads MSA

Industry employment data from all 134 Virginia localities, from 1990 to 2003, were retrieved from Virginia's Labor Market Access Database published by Virginia Employment Commission (VEC). Each locality could potentially have a maximum of 11 industry sectors. Employment growth rates (EG) are the dependent variable for Equation (11). From 1990 to 2003, the average industry employment grew by 36%, translating into 2.6% annual rates accordingly.

Table A2: Descriptive Statistics and Data Source

	Mean	Standard Deviation	Minimum	Maximum	Data Source
EG	1.4	0.7	0.1	5.6	VEC
LQ	1.1	2.0	0.0	42.3	Calculated
DI	0.7	0.2	0.1	1.0	Calculated
Emp (log terms)	6.0	1.8	0.0	11.4	VEC
Wage (log terms)	5.8	0.4	0.0	7.2	VEC
Pop (log terms)	10.1	1.0	7.9	13.6	Census
COLI	4.5	0.1	4.3	5.0	ACCRA
HS	0.7	0.1	0.4	0.9	Census
Tax	0.8	0.2	0.4	1.4	VA Tax
AP	3.2	0.6	1.4	4.1	VEDP

Same data sets are also used to calculate the initial specialization (*LQ*) and diversity index (*DI*) of each locality and industry sector at 1990. Those two variables are of central interests in this study. In summary, the average diversity index for all counties and cites is 66 %, with highest being 96% for Chesterfield County, and lowest being 5% of Buchanan County.

Those data sets are also used to calculate the initial employment (*Emp*) and wage (*Wage*) for each locality and industry sector at 1990. In 1990, the average size of the industry sector in each county was 1900. The average weekly wages for all industry was $342 per week in 1990. Both of those variables enter the model in log terms.

Population (*Pop*) and education attainment (*HS*) came from the 1990 Census data published by Census Bureau. Of all education attainment measurements, the model chose the percentage of work age population (Age 18 and above) with high school diplomas as the measure of the overall education attainment of the region. In 1990, in an average county in Virginia, about 66% of the adult population had a high school degree.

Cost of Living Index (*COLI*) is compiled by ACCRA-Council for Community & Economic Research. Those indexes are published each quarter for most MSA areas, as well as selected Micropolitan Statistical Areas. For rural counties that do not belong to MSA, COLI of Martinsville Micropolitan Statistical Area is used as a proxy of their COLIs in 1990.

The real estate tax data (*Tax*) are from Virginia Department of Taxation. Real estate tax is included to capture the tax burden of a business. The average real estate tax was 80 cents per $100 assessed value.

For infrastructure, only one variable is included, which is the access to Airport (*Ap*), measured by the distance from the center of a county to the nearest commercial airport. Variables such as interstate highway and railway were tested and their effects were not significant. The data are from Virginia Economic Development Partnership.

Appendix 2: General Discussion of Regression Results

This section will briefly discuss the effect of variables other than specialization and diversity on employment growth. The coefficient estimates are listed in Table A3. The discussion here uses results from Model 1, the finalized model specification.

The industry employment (*Emp*) at the 1990 has negative impact on the employment growth. These results are consistent with that of Glaser *et. al.* (1997) and Wheeler (2005). The coefficient (-0.26) is significant at 95% significant level. Larger industry usually grow slower, this seems to confirm the "S" shaped growth curve of typical firms.

The population (in log terms) in 1990 (*Pop*) seems to suggest that the places with larger population also grow faster. The coefficient is 0.25 and significant at 95% level. The model developed here are different from other studies where only manufacturing industries are studied (Henderson, *et. al.*, 1995), and population as a measure of market potential is important. Retails and services industries rely heavily on the local populations. It is not surprising those jobs gravitate to the population centers. As manufacturing industries are in decline, this variable will be more important. Hanink (2006) finds that population has a positive effect on economic growth.

Cost of living index (*COLI*) has a positive effect on employment growth. This seems to contradict to the claim that cost of living would reduce job creation. Several studies have shown that high COLI regions are usually areas with high quality of life, and are also areas with high entrepreneurial activities. Hanink (2006) also finds positive coefficient for COLI in his model.

Education attainment (*HS*) is an indicator of the overall human capital level of the region, as well as a measure of the skills and knowledge of the overall workforce (Wheeler, 2006; Hanink, 2006). This variable has a positive and significant impact on employment growth. The coefficient is positive (0.61) and significant at the 95% significance level, indicating that places with high education attainment have a better job growth.

Local real estate tax (*Tax*) has a negative and significant impact on the job growth of an industry, suggesting that businesses prefer to expand in places with low taxes. It is believed that this is an important variable in expansion or starts up decisions. More firms moving in created faster job growth.

Location Dummy variables reveal that the employment growth of three major MSA in Virginia did not grow faster or slower than the other regions of the state, as those coefficient estimates are insignificant.

The random effects for industry are solved. They summarized the industry specific factors that are unobservable, but are important in determining employment growth. They also capture the ongoing trend of the structural transformation of the American economy in the last decades. The following industries have a positive and significant effect on their employment growth: transportation, trade, and utility, professional and business service, education and health, and the leisure and hospitality sector. All those belong to service and high tech industries. Agricultural and information sectors have a negative and significant industry random effect

Table A3: Coefficient Estimate for Equation (11)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coefficient	T-Value	Coefficient	T-Value	Coefficient	T-Value	Coefficient	T-Value	Coefficient	T-Value	Coefficient	T-Value	Coefficient	T-Value
Intercept	-3.36	-3.13*	-0.11	-0.24	-2.52	-4.13*	0.11	0.24	-0.18	-0.39	-0.47	-0.90	0.43	0.90
LQ	0.03	2.64*	0.03	2.43*	0.03	2.82*	0.03	3.00*	0.03	2.38*	0.02	2.31*	0.02	2.38*
DI	0.20	1.8**	0.31	2.96*	0.15	1.46	0.15	1.39	0.34	3.04*	0.33	3.17*	0.24	2.31*
Emp	-0.26	-11.5*	-0.26	-11.9*	-0.26	-12.03*	-0.28	-12.39*	-0.26	-11.8*	-0.26	-11.77*	-0.26	-11.5*
Pop	0.25	8.65*	0.25	8.6*	0.24	8.23*	0.24	8.19*	0.25	8.61*	0.25	8.72*	0.23	7.91*
Wage	-0.07	-0.92	0.06	0.81	-0.10	-1.30	-0.03	-0.40	0.07	0.94	0.08	1.08	-0.02	-0.22
Social Economic Variables														
COLI	0.77	3.17*			0.78	5.9*								
HS	0.58	1.78*					0.88	4.45						
Tax	-0.24	-2.2*							-0.07	-0.78				
AP	0.09	2.24*									0.04	1.40		
Location Dummy Variables														
HR	-0.01	-0.18											0.03	0.53
NV	-0.04	-0.41											0.20	3.27*
RIC	0.09	1.61											0.12	2.47*
Industry Random Effects														
AG	-0.74	-4.98*	-0.74	-4.94*	-0.75	5.01*	-0.76	-5.05*	-0.74	-4.93*	-0.74	-4.92*	-0.73	-4.91*
CON	-0.04	-0.28	-0.05	-0.38	-0.04	-0.25	-0.04	-0.29	-0.06	-0.39	-0.06	-0.40	-0.05	-0.34
MAN	-0.19	-1.36	-0.21	-1.46	-0.18	-1.28	-0.18	-1.27	-0.21	-1.48	-0.21	-1.50	-0.20	-1.44
TTU	0.26	1.84**	0.27	1.9**	0.27	1.88**	0.29	1.97*	0.27	1.89**	0.27	1.89**	0.26	1.83**
INFO	-0.35	-2.41*	-0.38	-2.61	-0.34	-2.39*	-0.37	-2.55*	-0.38	-2.62*	-0.38	-2.63*	-0.36	-2.47*
FIN	-0.21	-1.54	-0.23	-1.65**	-0.21	-1.53	-0.23	-1.60	-0.23	-1.65**	-0.24	-1.66**	-0.22	-1.58
PBS	0.84	6.04*	0.83	5.84*	0.85	6.03*	0.84	5.87*	0.83	5.84*	0.83	5.83*	0.84	6.01*
EHS	0.44	3.1*	0.43	2.97*	0.45	3.16*	0.45	3.13*	0.42	2.94*	0.43	2.93*	0.43	3.02*
LH	0.19	1.26	0.28	1.87**	0.17	1.12	0.22	1.46	0.29	1.92**	0.30	1.97*	0.23	1.51
OSERV	-0.13	-0.92	-0.09	-0.65	-0.14	-1.00	-0.13	-0.88	-0.09	-0.62	-0.08	-0.59	-0.11	-0.79
PUB	-0.07	-0.54	-0.10	-0.71	-0.07	-0.49	-0.08	-0.57	-0.10	-0.73	-0.11	-0.75	-0.09	-0.63
-2 Res Log Likelihood	2811.90		2845.60		2813.40		2827.30		2848.00		2848.70		2843.20	
Sample Size	1431		1431		1431		1431		1431		1431		1431	
Average NAICS/Residual	0.18	0.39	0.19	0.41	0.18	0.40	0.19	0.40	0.19	0.41	0.19	0.41	0.18	0.40
Moran's I/P-Value	-0.0002	0.21	0.0019	0.0001	0.0001	0.06	0.0001	0.06	0.0010	0.0001	0.0018	0.0001	0.000233	0.0196
Note: *--significant at 95% level, **--significant at 90% level														

Appendix 3: Effects of Alternate Measure of Diversity

The effect of the Jacobs externality on location-industry employment growth is sensitive to the diversity index used[5]. Using different diversity measures has resulted in confusion in empirical literature (Wagner, 2000). This section explores the effect of alternative diversity indexes by using five indexes in econometric regression. Those indexes belong to two groups. One group of diversity indexes uses equal proportion employment as a standard, such as Ogive, Herfindahl and Dixit-Stiglitz indexes. Another group of index uses national industry structure as standard, such as Hachman and national average index[6]. In addition to the Hachman index, whose formula was presented earlier, the other four indexes are formulated below:

Ogive Index: $\sum_{i=1}^{I} \frac{\left(\frac{emp_i}{emp} - \frac{1}{I}\right)^2}{\frac{1}{I}}$, I is total number of industry

Herfindalh Index: $\sum_{i=1}^{I} \left(\frac{emp_i}{emp}\right)^2$, I is total number of industry

Dixit-Stiglitz Index: $\left(\sum_{i} \left(\frac{emp_i}{emp}\right)^{1/2}\right)^2$

National Average Index: $\sum_{i=1}^{I} \frac{\left(\frac{emp_i}{emp} - \frac{emp\_national_i}{emp\_national}\right)^2}{\frac{Emp\_national_i}{emp\_national}}$ I is total number of industry

I estimated the Model 1, using all five diversity indexes: Hachman, national average, Ogife, and Herfindahl, and Dixig-Stligtz diversity. The regression results are listed in Table A4. For all those models, changing diversity indexes has little effect on the coefficient estimates of

[5] The author is grateful for an anonymous referee for the suggestion.
[6] This paper did not test input-output index proposed by Deller-Wagner (1998), as the Virginia input-out data (from IMPLAN) can not be obtained free of charge.

location quotients and all other explanatory variables. This shows that the positive effect of MAR externality on industry employment growth is robust. The coefficients estimate for diversity indexes, however, is sensitive to which index is used. All diversity indexes using equal proportion as a standard have coefficient estimates that are insignificant. Two models using national industry structure as standard have coefficient estimates that are significant and have expected signs. For national average index, the coefficient estimate is negative and significant. Since the maximum diversity for national average index is 0, with less diversity being greater than zero, a negative sign implies that higher diversity promotes employment growth. For Hachman index, since diversity index varies between 0 and 1, with 1 being highest, the positive coefficient means that higher economic diversity can promote the employment growth.

Table A4: Regression Results with Different Diversity Index										
	Hachman Index		National Average Index		Dixit-Stiglitz Index		Ogife Index)		Herfindahl Index)	
Intercept	-3.36	-3.13*	-3.39	-3.16*	-3.40	-3.16*	-3.31	-3.02*	-3.32	-3.00*
LQ	0.03	2.64*	0.03	2.97*	0.03	2.43*	0.25	2.36*	0.02	2.36*
DI	**0.20**	**1.80****	**-0.03**	**2.85***	**-0.02**	**-0.87**	**0.00**	**-0.05**	**-0.01**	**-0.02**
Emp	-0.26	-11.50*	-0.26	11.63*	-0.25	-11.36*	-0.25	-11.34*	-0.25	-11.34*
Population	0.25	8.65*	0.27	8.99*	0.26	8.67*	0.25	8.61*	0.25	8.60*
Wage	-0.07	-0.92	-0.06	-0.83	-0.08	-1.05	-0.08	-1.02	-0.08	-1.02
Social Economic Variables										
COLI	0.77	3.17*	0.79	3.24*	0.82	3.27*	0.77	3.12*	0.77	3.12*
HS	0.58	1.78**	0.49	1.51	0.67	2.10*	0.69	2.14*	0.69	2.14*
TAX	-0.24	-2.20*	-0.22	-2.04*	-0.18	-1.73**	-0.19	-1.77**	-0.19	-1.77**
AP	0.09	2.24*	0.09	2.27*	0.10	2.44*	0.09	2.38*	0.09	2.38*
Location Dummy Variables										
HR	-0.01	-0.18	-0.02	0.24	-0.03	-0.41	-0.02	-0.36	-0.02	-0.36
NV	-0.04	-0.41	-0.04	-0.45	-0.05	-0.62	-0.05	-0.59	-0.05	0.59
RIC	0.09	1.61	0.08	1.53	0.09	1.72**	0.09	1.67	0.09	1.67
Industry Random Effects										
AG	-0.74	-4.98*	-0.75	-5.03*	-0.72	4.91*	-0.72	-4.91*	-0.72	-4.91*
CON	-0.04	-0.28	-0.04	-0.29	-0.04	-0.29	-0.04	-0.29	-0.04	-0.29
MAN	-0.19	-1.36	-0.19	-1.35	-0.19	-1.33	-0.19	-1.39	-0.19	1.39
TTU	0.26	1.84 **	0.27	1.86**	0.25	1.80**	0.25	1.80**	0.25	1.80**
INFO	-0.35	-2.41*	-0.35	-2.42*	-0.34	-2.39*	-0.34	-2.39*	-0.34	-2.39*
FIN	-0.21	-1.54	-0.21	1.53	-0.21	-1.54	-0.21	1.54	-0.21	1.54
PBS	0.84	6.04 *	0.84	6.01*	0.85	6.10*	0.84	6.10*	0.84	6.10*
EHS	0.44	3.10*	0.44	3.10*	0.43	3.10*	0.43	3.09*	0.43	3.09*
LH	0.19	1.26	0.20	1.30	0.18	1.21	0.18	1.21	0.18	1.21
OSERV	-0.13	-0.92	-0.13	-0.90	-0.13	-0.93	-0.13	-0.93	-0.13	-0.93
PUB	-0.07	-0.54	-0.08	-0.54	-0.07	-0.54	-0.07	-0.54	-0.07	-0.54
-2 Res Log Likelihood	2811.9		2812		2817		2817.80		2813.0	
Sample Size	1431		1431		1431		1431		1431	
Average NAICS/Residual	0.18	0.39	0.18	0.39	0.18	0.40	0.18	0.40	0.18	0.40
Moran I (P Value)	0.00	0.21	0.00	0.16	0.00	0.26	0.00	0.22	0.00	0.22
Note: *--significant at 95% level, **--significant at 90% level										

Using equal proportion index suggest that Jacobs externality does not exist. This seems to contradict with empirical evidence established by Glaeser et. al. (1992) and Henderson, et. al. (1995) that Jacobs externality is important to economic growth. That, coupled with the criticism that equal-proportion based diversity index lacks theoretical ration, ultimately convinced this study to use diversity index based on national economic structure.