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Abstract

In economic geography, there is a tendency to view regional economies as an inter-connected and endlessly evolving system. The way in which different sectors interact with each other in a region significantly influences the performance and future development of a local economy. This dissertation is comprised of three essays on U.S. regional economies, focusing on their resilience in the context of globalization as well as sector employment growth in recent decades. By investigating the impacts of entrepreneurship and industrial structure on the development and future pathways of a local economy, I seek to reveal details about the mechanisms of regional economic development and resilience from an evolutionary perspective.

The first two essays are about regional resilience against trade shocks. Different from previous literature in this area, these two articles study economic resilience from a new perspective of evolutionary economic geography, which emphasizes the ability to reconfigure economic structure and develop new growth pathways. The first essay proposes several mechanisms through which entrepreneurs can help to mitigate adverse trade shocks. Empirical results confirm that the adverse marginal impacts of trade shocks on job losses are dampened in regions with higher self-employment rates. The second essay studies how a regional economy converts the adverse impacts of import competition into a stimulus for developing new growth pathways. It is found that regions experiencing greater import competition are more likely to attract new industry entrants, which in turn may offer new growth opportunities and counteract the direct losses from trade shocks.

The third essay uses data on U.S. Commuting zones to investigate the heterogeneous impacts of industrial variety on the development of different sectors. The results suggest that industrial variety has a greater contribution to employment growth in two types of sectors: manufacturing industries that are technologically intensive, and geographically-agglomerated industries. This suggests the roles of industrial variety in contributing to growth are principally sector-based, and significantly depend on region-industry specific conditions.

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1 Self-employment and trade shock mitigation

Summary

This article investigates the moderating effects of entrepreneurial activity on the impact of trade penetration. Entrepreneurs may help to mitigate adverse trade shocks through several mechanisms, i.e., more flexible output structure, diversified economic portfolio, and higher knowledge spillovers from trade-induced R&D activities. Our empirical work embeds the analysis of entrepreneurship, measured using self-employment rates, into a framework of international trade and local labor markets. The empirical results show that the marginal impacts of Chinese import penetration on job losses are dampened in localities with higher self-employment rates, which suggests self-employment or entrepreneurial activities can mitigate the adverse impacts of trade penetration from low-income countries. Our study provides a novel perspective on entrepreneurs' benefits on economic well-being: besides their direct contribution to economic growth documented in earlier research, they can also enhance the resilience of a local economy in the face of external shocks.

KEY WORDS: self-employment, entrepreneurship, trade shocks, economic resilience

JEL CLASSIFICATION: L26, R11, F16, F61

1.1 Introduction

An important phenomenon in international trade during the past several decades has been the rapid rise of newly industrialized countries accompanied by growth in their exports to high-income economies. While economic theory indicates that trade in free markets increases welfare, one of the main debates about the impacts of international trade concerns the distribution of benefits and costs among different regions, sectors, and labor groups (e.g., Bustos, 2011; Davis, 1998; Krishna et al. 2012; Meckl, 2006; Melitz, 2003). For developed countries, import competition from low-income economies may impact the labor market more than other trade shocks (P. R. Krugman, 2008). For US local labor markets, recent studies suggest that increasing exposure to imports from developing countries can result in negative short run shocks (e.g., Autor et al. 2013; Leichenko & Silva, 2004). However, little attention has been paid to the role of localities' idiosyncratic features in shaping their response to import competition. National sub-regions with higher shares of industries at a comparative trade disadvantage will likely experience short run labor market losses, while regions more able to adjust their labor markets will better adapt to trade shocks and suffer smaller losses. Therefore, it is possible that regions with certain characteristics suffer less from the same trade shock than others.

Among the factors that may influence a locality's ability to mitigate trade shocks, this paper focuses on entrepreneurship, which we measure using self-employment rates. Self-employment rate is widely used as a proxy for the level of entrepreneurial activities (e.g., Acs et al. 2008; Glaeser & Kerr, 2009; Glaeser, 2007; Goetz & Shrestha, 2009; Rupasingha & Goetz, 2013). In this literature the connection between entrepreneurial activities and economic growth is currently being debated widely. Theories indicate that entrepreneurs can promote economic development by exploiting potential entrepreneurial opportunities or by taking advantage of knowledge spillovers (Acs et al. 2008). The correlation between self-employment and economic growth in US local economies has been confirmed in many recent empirical studies (e.g., Goetz & Rupasingha, 2009; Henderson & Weiler, 2009; Rupasingha & Goetz, 2013; Stephens & Partridge, 2011). However, beyond the statistically significant correlations between self-employment and economic development, there is little empirical evidence about *how* self-employment contributes to local economic well-being. Our study provides a new perspective for interpreting the role of self-employment in regional economic growth and development. Given entrepreneurs' characteristics, more entrepreneurial regions may be better able to exploit opportunities, have more diversified economic portfolios, and enjoy greater market vitality. Thus we hypothesize that in regions with higher self-employment shares the negative impact of import shocks on the labor market will be smaller.

In this paper we investigate how the share of the self-employed in the labor force affected the impacts of rising Chinese imports on US counties during 2000-2007. Our empirical approach mainly builds on previous work that investigates the impacts of international trade on local labor markets (Autor et al., 2013; Borjas & Ramey, 1995; Chiquiar, 2008; Edmonds et al., 2010; Kovak, 2013; Topalova, 2010). A key approach in these papers is to measure local exposure to trade shocks using a region's industrial employment structure. The regional unit of analysis in this paper is the county, and so we measure import change in a county by weighting each industry's national level import change by the county's employment specialization, as described in more detail in section 3.

For trade data, we focus on the increase in Chinese imports during 2000-2007. As Autor et al. (2013) indicate, first, the increase in Chinese imports made up most of the US import increases from developing countries during this period; and second, China's trade advantage was largely due to its increasing productivity and/or lowered trade barriers, which were exogenous to US labor markets, allowing for greater efficiency in estimation. As to the estimation strategy, an important concern is about possible endogeneity of Chinese imports in the local economy. Autor et al. (2013) study the impacts of Chinese import penetration on US Commuting zones and address this "endogeneity" issue (without explicit statistical testing) by instrumenting the increase in Chinese imports to the US with the increase of Chinese imports to other high-income countries. However, Autor et al. (2013) appear to confuse endogeneity at the national level with what may occur at the local level, as it is implausible that a local shock would affect overall Chinese imports to the US, especially for the local economy as small as a county in our study. As shown in the appendix of this chapter, a Wu-Hausman test with our county level data indeed confirms that we cannot reject the "no endogeneity" hypothesis for either metro or non-metro counties. Therefore, we base our empirical work on OLS estimation.

Our empirical results show that as the self-employment rate increased over the period leading up to the recent Great Recession, wage and salary job growth declined but the negative impact of import penetration on job creation was attenuated. Therefore, in those counties with higher shares of self-employed, the detrimental marginal impact of Chinese import penetration on job losses was smaller. The contribution of this paper is two-fold. First, for the stream of work on the impacts of import competition on local labor markets, our results provide strong evidence that within a country different sub-regions could have varied labor market responses to growing trade exposure, and that local entrepreneurial activity or self-employment helps the locality absorb trade shocks. Second, for the domain of entrepreneurship studies, while most existing empirical studies focus on the direct causal relationship between entrepreneurship level and economic variables such as employment, wage, income, etc., our approach examines whether self-employment can help localities to mitigate negative economic impacts from external shocks. And our findings provide a new perspective for interpreting how entrepreneurs contribute to regional economic well-being, i.e., they may also enhance the resilience of local labor markets.

The remainder of this article is organized as follows. In section 1.2, we provide a background on entrepreneurship and local labor markets, and discuss possible mechanisms through which self-employment influences local labor market responses to trade shocks. In section 1.3 we describe our empirical method and data. The estimation results are reported in section 1.4. Section 1.5 tests the robustness of the empirical results with alternative model specifications. Section 6 discusses our main findings and concludes the whole paper.

1.2 Entrepreneurs, local labor markets, and trade shocks

Although the relationship between self-employment and long-term regional development has been examined intensively in the recent literature, few studies consider possible interactions with international trade. This study, to the best of our knowledge, is the first to investigate the role of self-employment in shaping localities' ability to cope with exogenous shocks such as increasing trade penetration. And we suggest that entrepreneurs may reduce the vulnerability of a local economy to trade shocks through the following mechanisms.

First, entrepreneurial activities can help a local economy to more effectively respond to changing market opportunities brought about by trade. Trade liberalization will reveal a country's comparative advantages on a larger market scale, and cause fluctuations for local business. Existing market supply-demand systems of regional economies may become imbalanced. For example, when more manufactured products with low-skill content are imported from developing countries at lower prices, the demand for comparable goods produced in the US declines. Meanwhile, when local residents spend less buying these imported merchandises, their demand for high tech products and non-tradable goods/services that cannot be imported may increase. US regional economies have also been found to adapt to trade shocks mainly through structural adjustments in output (Hanson & Slaughter, 2002). In this context of *creative destruction*, entrepreneurship plays an important role (Schumpeter, 1932). Entrepreneurial activities that bring about innovations and provide more new products (Acs & Attila, 2005; Acs & Szerb, 2007) help a region to meet new market demand and rebalance the local economy. Many recent studies also suggests that entrepreneurs play essential roles in an economy's structural change by imposing competition on incumbent firms, creating new business, and absorbing surplus workers from shrinking industries (Fritsch, 2013; Gries & Naudé, 2010). Thus we expect that regions with higher shares of entrepreneurs will be able to more effectively rebalance the economy and deal with the adverse shocks of increasing trade exposure, and exhibit better economic performances.

In addition, greater self-employment or entrepreneurial activity are associated with more economic diversity and activity in general within local economies (Eliasson, 1991; Silverberg et. al., 1988). Such activity may include filling of "market gaps" (Leibenstein, 1968) or simple arbitrage (Kirzner, 1997), which targets market niches of the local economy, or Schumpeterian innovation, which is aimed at creating new businesses patterns. As a result, the self-employed may operate businesses that are different from those of dominant incumbent large firms and they increase the diversity of the local economy. Prior studies also show that a diversified economic structure has greater resilience and can better adjust to external shocks due to portfolio effects (e.g., Dissart, 2003; Frenken et al. 2007; Kaufmann, 1993; Malizia & Ke, 1993).

The third mechanism involves two facets -- increasing R&D activities that are induced by trade competition, and entrepreneurs' innate capabilities of taking advantage of spillover effects. First, comparative advantage theory indicates that trade liberation will drive a country to focus more on the products in which it outperforms other countries. Thus it is reasonable to expect that when facing greater competition from low-income countries like China, developed countries' firms will increase R&D activities and seek to concentrate more on high-tech products or services, which cannot be easily challenged by Chinese competitors. This phenomenon was in fact recently observed. Bloom et al. (2013) find that Chinese import competition significantly increased R&D and patenting activities in European countries during 1996-2007. On the other hand, the role of entrepreneurs in taking advantage of R&D spillovers has been widely discussed recently, and it is believed that entrepreneurs can take advantage of spillovers from incumbent firms' R&D activities and help to more effectively commercialize them (Acs et al., 2008; Braunerhjelm et al., 2009; Qian & Acs, 2011). As a consequence, when Chinese import competition stimulates more R&D and patenting activities in a region, if there are also higher levels of entrepreneurial activities in the local economy, the economic outcomes of those R&D and patenting activities are superior, which counteract losses from trade shocks.

To summarize, although the roles of self-employment in helping to mitigate adverse impacts of trade penetration have not been theoretically and systematically analyzed before, we suggest that many aspects of the nature of entrepreneurship can contribute to local economic resilience. In particular, the presence of self-employed or entrepreneurs has been shown to be positively associated with local economic adaptability, diversity, and technology spillovers. In next section we design an empirical approach to investigate this moderating effect of entrepreneurial activities in trade-induced losses in local labor markets.

1.3 Empirical approach and data

1.3.1 Measure of import exposure

Statistics for import changes at the US regional level such as counties are not available from any open access database. Thus our measure of counties' trade exposure is indirectly derived based on local industry specialization, an approach widely used in recently studies (Autor et al., 2013; Edmonds et al., 2010; Kandilov, 2009; Kovak, 2013; Topalova, 2010). Specifically, we calculate the following *change in Chinese Import Per Worker* (ΔIPW thereafter) to proxy local trade exposure to import competition from China:

$$\Delta IPW_{US,i} = \frac{1}{L_i}\sum_j \frac{L_{i,j}}{L_{US,j}}\Delta M_{US,j} \tag{1.1}$$

In (1.1), $\Delta M_{US,j}$ is import change in sector j for the US during a certain period; $L_{i,j}$ is employment of sector j in county i; $L_{US,j}$ is employment of sector j in the entire US; and L_i is total employment in county i. Therefore, $\Delta IPW_{US,i}$ measures the import shock (in thousand $) per worker in county i during the period under study. A greater $\Delta IPW_{US,i}$ means higher pressure from import competition on the local labor market. The time frame of analysis is 2000-2007, the period after Chinese imports began to prominently increase and before the financial crisis. Thus the import change $\Delta M_{US,j}$ is the difference from 2000 to 2007, and $L_{US,j}$, L_i, and $L_{i,j}$ are initial year (2000) values.

1.3.2 Empirical method and data

We start with a cross-sectional growth model shown in (1.2) which, as in previous literature, can be used to investigate the impacts of import penetration or other trade policies on local labor markets. Δy_i is a proxy for local labor market performance, such as the change in poverty rate, employment, or wage. Δx_i is the trade-related variable to be investigated, which could be a tariff change or, as in our case, import shock ΔIPW; $cv_{k,i}$ are other control variables and θ_k their coefficients.

$$\Delta y_i = \beta_0 + \beta_1 \Delta x_i + \sum_k \theta_k cv_{k,i} + \epsilon_i \tag{1.2}$$

With a model similar to (1.2), Kovak (2013) finds that in Brazil those regions whose workers faced greater loss of tariff protection experienced more wage cuts. Topalova (2010) investigates the relationship between trade liberalization and poverty in India, and indicates that poverty rates fell more slowly in rural regions where production sectors were exposed more to import penetration. Autor et al. (2013) find that commuting zones in the US that had undergone higher Chinese import exposure had higher unemployment, lower labor force participation, and more wage cuts during 1990-2007, which suggests trade competition from China's imports resulted in negative shocks to US local economies and labor markets. Given these results, we embed self-employment into this trade shock vs. local economy paradigm as in (1.2), and propose that regions with higher self-employment shares can better mitigate the adverse shocks of import competition. Or:

Proposition. *In regions with higher shares of entrepreneurs/self-employed, the marginal impacts of Chinese import penetration on job losses are moderated.*

We estimate the following model to test this proposition empirically:

$$\Delta y_i = \beta_0 + \beta_1 \vartriangle IPW_{US,i} + \beta_2\left(\vartriangle IPW_{US,i} * self\_emp_i\right) + \beta_3 self\_emp_i + \sum\nolimits_k \theta_k cv_{k,i} + \epsilon_i \tag{1.3}$$

In (1.3), Δy_i is a proxy for the local labor market performance of a county, for which we use wage-and-salary employment. Although the direct impacts of import competition are mostly on tradable goods or manufacturing sectors, here we are using the employment data for the entire labor market to capture not only the direct impacts of trade shocks but also the multiplier effects and indirect impacts of entrepreneurship on employment (Fritsch & Noseleit, 2013a, 2013b). $\vartriangle IPW_{US,i}$ is the change in Chinese imports per worker as defined in (1), and $self\_rate_i$ is the share of self-employment in total employment at the initial year 2000, which is calculated using the US Census data[1]. In this model, the net coefficient of trade penetration $\triangle IPW_{US,i}$ is $(\beta_1 + \beta_2 self\_emp_i)$, which should be negative given that trade shocks tend to adversely affect local labor markets in general. However, if the above proposition holds, i.e., self-employment mitigates an import shock's negative impact on the local labor market, then we expect β_2>0, which means in more entrepreneurial regions the net effects of trade shocks are smaller in scale.

To calculate the import shock $\triangle IPW_{US,i}$ from (1.1), data of Chinese imports to the US $M_{US,j}$ come from the US Census Bureau's US International Trade Statistics database[2]; data for $L_{i,j}$, $L_{US,j}$, and L_i for different periods are from the US Census Bureau's County Business Patterns (CBP). For the local economic performance proxy Δy_i in model (1.3), we use log change of employment (wage-and-salary job) during 2000-2007, which is from the Bureau of Economic Analysis (BEA)[3]. For calculating the ratio of self-employment in total employment, the data of self-employment and total employment come from the US Census 2000 database[4]. We also include some other control variables of local demography in model (1.3). They are the share of college educated people in total population, the ratio of white people, the age composition of local population, and the number of local population. All these control variables are the initial year (2000) values and are also derived from the US Census 2000 database.

1 In US census data 2000, the total employment consists of four parts: wage and salary employment in private sectors, government employment, self-employment, and un-paid family workers.
2 http://www.census.gov/foreign-trade/data/
3 http://www.bea.gov/regional/index.htm
4 http://www.census.gov/main/www/cen2000.html

1.3.3 Industrial structure

Besides the local demographic control variables mentioned above, other important structural variables need to be controlled for given the specification of our model and the trade shock measure. They are the local industrial structure, firm size effects, and the distribution of entrepreneurs between traded and non-traded sectors, which we discuss in the following three sub-sections.

The industrial structure of local economies must be controlled for in the model due to two concerns. First, self-employment rates vary significantly between different sectors, and these sectors are likely to have different growth rates. If industry shares are not appropriately accounted for, the empirical results may just reflect the impact of industrial composition on local economic growth rather than that of entrepreneurial activities. Second, because we estimate a conventional growth model using cross-sectional data, our results could be affected by differential growth rates arising as fixed effects (such as growth in Detroit persistently lagging behind that in Phoenix). Sector productivity differences are the most important fixed effects that we are concerned with. In our model the measure of trade penetration is primarily based on import values, and thus we would otherwise miss regional productivity growth variations that arise from different industrial structures. In particular, the variations within non-traded sectors are not well represented in the trade penetration measure of equation (1.1). Given these concerns, we also control for lagged regional industrial structure of counties. We calculate the employment shares of the ten SIC industry divisions in each county for the year 1990 as industrial structure control variables in our model.[5]

1.3.4 Firm size effects

While self-employment is most commonly used as a proxy for entrepreneur activities in similar studies, it is also strongly correlated with average firm size in the local economy. A higher ratio of self-employed establishments, with only one employer/employee, reduces the average employment size of local firms. On the other hand, previous literature suggests that the firm size of tradable sectors affects the impacts of trade shocks. Bernard & Jensen (1995) point out that large firms more likely engage in international trade. Other researchers who focused on the relationship between firm size and productivity found that smaller firms, which usually have lower productivity, are more likely to be driven out when faced with rising import penetration (Bernard et al., 2003; Melitz, 2003). However, Holmes & Stevens (2014) propose an opposite mechanism that smaller firms, which focus their business more on customized goods and services for local markets, are less likely to be impacted by increasing imports of labor-intensive goods from developing countries.

The existing literature thus provides competing implications for the relationship between firm size and the impacts of trade shocks. The purpose of this paper is not to resolve this debate, but we need to control for this possible firm size effect so as to ensure that what our model tests is the role of self-employment in mitigating trade shocks that is due to entrepreneurship rather than firm size. The firm size variable $firm\_size_i$ here is measured as the average number of employment per establishment, which is also calculated from the County Business Pattern

5 The SIC industry division codes can be found in http://www.naics.com/sic-codes-industry-drilldown/. County employment data of SIC industries are from the County Business Patten (CBP) dataset mentioned above. More descriptive information about the industrial structure control variables is shown in Section 1.7 Data Appendix.

(CBP) 2000.

1.3.5 Distribution of self-employment between traded and non-traded sectors

Measuring entrepreneurial activities as the ratio of self-employment in total local employment ignores the distribution of self-employers across different industries, specifically for traded and non-traded sectors. Earlier studies about trade liberation also suggest that traded and non-traded sectors play different roles in the presence of import shocks and should be treated differently (see, for example, Kovak, 2013; Topalova, 2010). In section 2 we discussed several possible mechanisms that make entrepreneurial regions more resistant to trade shocks, i.e., smoother structural change, a more diversified economic portfolio, and knowledge spillovers. All of these mechanisms function on a sector-basis, and the share of entrepreneurs in traded industries may have a more direct and immediate impact in the local economy in terms of attenuating the effects of trade penetration.

Data limitations do not allow us to examine these ideas directly for the self-employed. However, another data set, the non-employer statistical series (US Census Nonemployer Statistics[6]), which is highly correlated with the self-employment series[7], does provide industry sector detail and this allow us to create a tradable vs. non-tradable nonemployer data series as a self-employment proxy at the county level for 2000. Nonemployers are small businesses that have no paid employees and are subject to federal income tax, and are different from and yet similar to self-employers[8]. We create a proxy variable consisting of the share of non-employers

6 https://www.census.gov/econ/nonemployer/index.html

7 The covariance between the number of self-employment and non-employer is 0.976 at the county level.

8 In particular, "most nonemployers are self-employed individuals operating unincorporated businesses (known as sole proprietorships), which may or may not be the owner's principal source of income." For more details about the definitions and data of nonemployer, see https://www.census.gov/econ/nonemployer/index.html.

in the traded sector among all non-employers in a county, and then include it as a control variable into equation (1.3). Table 1.1 provides descriptive statistics for all of the above variables, except for the industrial structure variables which are shown in the online data appendix.

Table 1.1 Descriptive statistics for county labor markets (metro and non-metro counties)

Variable	Metro		Non-metro	
	M	SD	M	SD
Change in Chinese import per worker ($\Delta IPWus,i$), 2000-2007 / (thousand $)	4.38	2.18	4.62	2.85
Log change in the count of W&S employment, 2000-2007 / (100 × log points)	7.28	13.70	0.55	12.61
Share of self-employment in total employment, 2000 / (%)	6.99	2.28	11.14	5.18
Percentage of college educated population, 2000 / (%)	20.51	9.42	14.40	5.73
Percentage of white people, 2000 / (%)	82.64	15.06	85.38	17.26
Percentage of population aging 50-59, 2000 / (%)	11.42	1.41	11.80	1.57
County population, 2000 / (10 thousand)	21.85	47.88	2.38	2.28
Average firm size, 2000 / (employment per establishment)	14.09	5.07	11.02	4.43
Share of nonemployers in traded sectors, 2000 / (%)	1.66	0.84	1.59	1.45

Data Source: $\Delta IPW_{us,I}$ are calculated by authors with equation (1); wage-and salary employment data are from the BEA; demographic control variables are calculated from the US Census 2000; firm size data is calculated from CBP 2000; non-employer data is from US Census Nonemployer Statistics.

1.4 Empirical results

In this section we estimate the model of equation (1.3) for metro and non-metro counties separately. The dependent variable Δy_i is calculated as the log value in 2007 minus the log value in 2000, so that the regression coefficients provide the percentage change from the initial year. For ease of interpretation, in all regressions of this paper the share of self-employment $self\_emp_i$ and the import shock $\Delta IPW_{US,i}$ are calculated as deviations from their median values of the regression samples. OLS results of model (1.3) are shown in Table 1.2 for metro and non-metro counties respectively. Both columns include all the control variables listed in Table 1.1 as well as the lagged industrial structure control variables. And we also include state dummies to control for regional fixed effects.

In Table 1.2 the coefficients of $\Delta IPW_{US,i}$ are negative and statistically significant in both columns, which means counties with higher import increases from China had less employment growth compared with counties not experiencing such increases. More importantly, the coefficients of cross-term $\left(\Delta\, IPW_{US,i} * self\_emp_i\right)$ are statistically significant and positive for both metro and non-metro counties, which means the net marginal impacts of Chinese import shocks, expressed as $(\beta_1 + \beta_2 self\_emp_i)$, are smaller in the regions that have higher shares of entrepreneurs. Thus these results confirm our earlier proposition that in counties with higher shares of entrepreneurs/self-employment, the adverse impacts of trade shock on local labor market are dampened.

Table 1.2 Cross effects of self-employment and import shocks in county labor markets (2000-2007)

DepVars: 100×ΔLog (Counts of Wage-and-Salary Employment)

	(a) Metro counties	(b) Non-metro countries
Change in Chinese import per worker, ($\Delta IPWus,i$)	-0.766***	-0.558***
	(0.176)	(0.140)
Cross-term, ($\Delta IPWus,i*self\_emp_i$)	0.199***	0.085***
	(0.051)	(0.024)
Share of self-employment in total employment	-1.016***	-0.199**
($self\_emp_i$)	(0.327)	(0.085)
Percentage of college educated population	0.460***	0.252***
	(0.097)	(0.054)
Percentage of white people	0.222***	0.094**
	(0.078)	(0.035)
Percentage of population age 50-59	-1.210*	-0.281
	(0.664)	(0.249)
Population	-0.001	0.597***
	(0.008)	(0.164)
Ave. firm size	-0.677***	-0.286*
	(0.142)	(0.148)
Share of non-employers in traded sector	1.177*	0.831***
	(0.662)	(0.205)
Lagged industrial structure (1990)	Yes	Yes
State dummies	Yes	Yes

Notes: N=1051 for metro counties and N = 1987 for non-metro counties. Robust standard errors clustered by state are in parentheses. $\Delta IPW_{us,I}$ and $self\_emp_i$ are calculated as deviations from their median values respectively (split by metro and non-metro counties respectively).
*Level of statistical significance: *** $p<0.01$; ** $p<0.05$; * $p<0.10$.*

Based on the results of Table 1.2 and the distribution of self-employment rates over counties, we can retrieve the point estimates of the impacts of trade shocks over the spectrum of self-employment rates. Since in our regressions the share of self-employment is calculated as the deviation from its median value, the coefficient of $(\Delta IPW_{US,i})$ in Table 1.2 should be interpreted as its actual point estimate for a county with the median self-employment rate. In

Table 1.3 we calculate the marginal impacts of a one thousand dollars change in Chinese imports per worker on labor markets at the 25%, 50%, and 75% self-employment rate percentiles for metro and non-metro counties respectively. We can see that for both metro and non-metro counties, the trade-induced job losses of counties at the 75% percentile of self-employment rate are much lower than those in counties at the 25% percentile. It should be noted that Table 1.3 describes the mitigating effects of self-employment on trade shocks, rather than the net impacts of self-employment on county employment growth. Given that the coefficients of self-employment in Table 1.2 are significantly negative, only in cases with sufficiently high exposure to trade shocks will self-employment increase overall employment growth in the period 2000-2007. In future research it would be important to examine how stable this relationship is over time.

Table 1.3 Marginal impacts of $1,000's change in Chinese import per worker on employment growth for counties with different self-employment rates (2000-2007)

	(a) Metro counties	(b) Non-metro counties
	Calculated from Table 2(a)	Calculated from Table 2(b)
At 25% percentile of self-employment rate	-0.979%	-0.747%
At 50% percentile of self-employment rate	-0.766%	-0.558%
At 75% percentile of self-employment rate	-0.428%	-0.251%

Note: Author calculations, based on the results of Table 2. The self-employment rate at the 25%, 50%, and 75% percentile are 5.36%, 6.43%, and 8.13% in metro counties, and are 7.54%, 9.76% and 13.37% in non-metro counties.

1.5 Robustness analysis

In model (1.3) we assume that regions with different self-employment rates experience varied impacts from trade shocks. However, it is possible that not only the self-employment rate but also other factors influence this trade impact.

Our first concern is the higher order impacts of import exposure. In model (1.3) only the linear form of import change per worker $\Delta IPW_{US,i}$ is included. In addition, we noticed that for counties the self-employment rate has a weak but significant correlation with the trade penetration.[9] Thus it is possible that the cross-term of $(\triangle IPW_i * self\_emp_i)$ merely picks up the explanatory power of the squared term of $\triangle IPW_{US,i}$. Another potential problem is that other characteristics of counties may also affect the actual coefficient of import exposure on the local labor market, such as the demographic control variables listed in table 1.1. Then the actual coefficient of $\Delta IPW_{US,i}$ would be:

$$\beta_{actual} = \beta_1 + \beta_2 self\_emp_i + \gamma \Delta IPW_{US,i} + \sum_k \alpha_k cv_k$$

Thus model (1.3) becomes:

$$\Delta y_i = \beta_0 + \beta_{actual} \triangle IPW_{US,i} + \beta_3 self\_emp_i + \sum_k \theta_k cv_{k,i} + \epsilon_i \qquad (1.4)$$

And the testable form of (1.4) is:

9 Regression of $\Delta IPW_{US,i}$ on the self-employment rate yields: coeff=-0.086, t=-5.3, R2=0.04.

$$\Delta y_i = \beta_0 + \beta_1 \triangle IPW_{US,i} + \beta_2 \left(\triangle IPW_{US,i} * self_{emp_i}\right) + \gamma \Delta IPW_{US,i}{}^2 + \sum_k \alpha_k (cv_{k,i} * \triangle IPW_{US,i}) + \beta_3 self\_emp_i + \sum_k \theta_k cv_{k,i} + \epsilon_i \quad (1.5)$$

where the $(cv_{k,i})$ include all the demographic control variables in Table 1.1. The regression results of model (1.5) for metro and non-metro counties are shown in Table 1.4. After including the squared term of $\Delta IPW_{US,i}$ and other cross-effects that may influence the model, the cross-effects of self-employment rate and $\Delta IPW_{US,i}$ remain significantly positive and are of similar magnitude, consistent with results in Tables 1.2.

Table 1.4 Sensitivity analysis of the cross effects of self-employment and import shocks in county labor markets (2000-2007)

DepVars: 100×ΔLog (Counts of Wage-and-Salary Employment)

	Metro counties		Non-metro counties	
	(a)	(b)	(c)	(d)
Change in Chinese imports per worker, (Δ*IPWus,i*)	-0.441	1.808	-0.812***	-3.531***
	(0.318)	(3.130)	(0.197)	(1.303)
Cross-term, *(ΔIPWus,i*self_emp$_i$)*	0.251***	0.287***	0.081***	0.052*
	(0.054)	(0.061)	(0.025)	(0.030)
Share of self-employment in total employment	-0.997***	-0.997***	-0.204**	-0.219**
	(0.318)	(0.315)	(0.084)	(0.084)
$\Delta \boldsymbol{IPW_{US,i}}^2$	-0.036*	-0.033*	0.024*	0.032**
	(0.019)	(0.019)	(0.012)	(0.013)
All cross-terms of $(\boldsymbol{cv_{k,i}} * \triangle \boldsymbol{IPW_{US,i}})$		Yes		Yes
Lagged industrial structure (1990)	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes

Notes: N=1051 for metro counties and N = 1987 for non-metro counties. All columns include the control variables in Table 1. Robust standard errors clustered by states are in parenthesis.
*Level of statistical significance: *** p<0.01; ** p<0.05; * p<0.10.*

1.6 Discussion and concluding remarks

This paper imbeds the analysis of self-employment into a framework of trade shock and local labor market, in order to study the roles of entrepreneurial activities in the resilience of local economy. Our empirical results reveal that there are significantly positive cross-effects of trade-penetration and self-employment on local employment growth during 2000-2007, which suggests that self-employment in a county has a significant role in mitigating the negative impacts of import shocks on local labor market. Our empirical results are robust when we control for the lagged industrial structure, the firm size effects, and the distribution of entrepreneurs between traded and non-traded sectors. These findings confirm the benefit of entrepreneurs or the self-employed in promoting local economic development. And our approach provides a new perspective about entrepreneurial activities' indirect impacts on local economy, i.e., self-employment helps a region to mitigate the adverse impacts of external shocks and thus contributes to local economic resilience.

Due to the lack of available self-employment data at the industrial level, we did not distinguish the roles of self-employment in different kinds of sectors such as traded vs. non-traded. However, we are able to use non-employer data as a proxy variable to investigate separately the effects of self-employment in the tradable sectors. Once data at finer industrial levels become available, it would be important to examine the potential trade-mitigating impacts of entrepreneurial activities in greater detail. Recent studies confirm that the economic consequences of entrepreneurship are largely sector-based, and strongly depend on an industry's life cycle, innovation intensity, and intra-industry competitions (R. Boschma &

Frenken, 2011; Fritsch & Noseleit, 2013a, 2013b; Fritsch, 2011; Low & Isserman, 2013). Thus investigating the roles of self-employment/entrepreneurs in regional economic resilience at disaggregate industrial levels will likely contribute to a deeper understanding of entrepreneurship.

Another future extension is towards a theoretical and systematic framework of entrepreneurship's roles in enhancing regional economic resilience. In this paper we suggest several possible mechanisms that explain why self-employment can mitigate trade shocks on local labor market, i.e., regions with higher shares of self-employment may have greater flexibility in the output markets and have a more diversified industrial portfolio, and can more effectively exploit knowledge spillovers from incumbent firms' R&D activities stimulated by trade competition. We were unable to find direct evidence in the literature that these mechanisms have actually been observed systematically, but this may be accomplished by future studies.

Our findings also have important implications for policy makers and local economic development practitioners in coordinating local development strategies and trade-related labor market policies. In the US, in order to promote local economic prosperity, governments have provided various incentives such as subsidies or tax breaks to support local self-employment (Goetz and Partridge 2010; Goetz et al. 2011). Also, as a result of extensive labor market shocks resulted from increasing imports from developing countries, policies such as the Trade Adjustment Assistant (TAA) program have been enacted to address trade-related job loss. Our empirical results suggest that local entrepreneurial activities or self-employment can also reduce adverse impacts of trade shocks, and it is advisable to better coordinate these two kind of policies in order to achieve greater policy efficiency.

1.7 Appendix A. Data

1.7.1 Industry structural control variables in the lagged year 1990

As discussed in section 1.3.3, we need to control for lagged regional industrial structure of counties. We calculate the employment shares of the ten SIC divisions in each county for the year 1990 from the County Business Pattern dataset. The division is the highest level of the SIC classification, and includes these ten industry groups:

Table 1.5 SIC divisions

Division	SIC Code Range	Industry Title
A	01-09	Agriculture, Forestry & Fishing
B	10-14	Mining
C	15-17	Construction
D	20-39	Manufacturing
E	40-49	Transportation, Communications, Electric, Gas & Sanitary Services
F	50-51	Wholesale Trade
G	52-59	Retail Trade
H	60-67	Finance, Insurance & Real Estate
I	70-89	Services
J	91-99	Public Administration

Source: United States Department of Labor. *https://www.osha.gov/pls/imis/sic_manual.html*

In our model, the measure of trade shock ΔIPW is derived based on the local industry specialization of traded sectors, as shown in equation (1.1). This means the information on the structure of traded industries has already been incorporated into the trade shock measure. And the trade shock ΔIPW can be expressed as a function of the employment shares of traded sectors. Thus, in order to avoid strong multi-colinearity, we aggregate the three traded sectors (A, B, and D) of Table 1.5 into a single sector of "Traded sector". Table 1.6 shows the adjusted eight SIC divisions that we include in our model as industrial structure control variables as well as their descriptives for metro and non-metro counties.

Table 1.6 Industrial structure control variables and descriptives (1990)

(% of county employment)

Industry Title	Metro		Non-metro	
	M	SD	M	SD
Traded sector	26.13	13.90	28.91	17.08
Construction	6.55	4.26	4.85	4.13
Transportation, Communications, Electric, Gas & Sanitary Services	5.65	4.64	5.80	5.26
Wholesale Trade	5.69	3.28	6.67	5.82
Retail Trade	23.97	6.40	24.68	8.38
Finance, Insurance & Real Estate	5.47	2.95	5.12	3.48
Services	26.03	8.88	23.07	10.00
Public Administration	0.51	0.53	0.89	1.70

Data source: County Business Pattern 1990

1.7.2 Wu-Hausman test for the endogeneity of import penetration at the county level

The OLS estimation for the Wu-Hausman test is based on the original model of equation (1.3), which includes the full set of control variables of Table 1.1 as well as the lagged industrial structure and the state dummies. Then for the 2SLS method, we follow Autor et al. (2013) and instrument the $\Delta IPW_{US,i}$ using contemporaneous changes of Chinese imports to other high-income countries, $\Delta IPW_{o,i}$, which is calculated as:

$$\Delta IPW_{o,i} = \frac{1}{L_{i,t-1}} \sum_j \frac{L_{i,j,t-1}}{L_{us,j,t-1}} \Delta M_{o,j} \tag{1.6}$$

Equation (1.6) differs from the expression of $\Delta IPW_{US,i}$ in two ways. First, import changes $\Delta M_{o,j}$ are for other developed countries. In our model we include: Japan, Australia, France, Germany, and Finland. These five high-income countries together have an economic scale comparable to the US, and all had relatively stable macro economies during 2000-2007. And they are all non-North American countries so that they are suitable instruments for our analysis. The second difference is that, in equation (1.6) the three labor-related variables L_i, $L_{i,j}$, and $L_{us,j}$ are all taken as one decade lag values (1990), as the subscript *t-1*indicates. Thus the 2SLS estimation for the Wu-Hausman test is based on the original model of equation (1.3) as described above, with the trade shock $\Delta IPW_{US,i}$ instrumented by $\Delta IPW_{o,i}$.

Based on these settings, the Wu-Hausman tests yield (p=0.1863) for metro counties and (p=0.9243) for non-metro counties, and we cannot reject the *H0* that there is no endogeneity.

1.8 Appendix B. Commuting zone level analysis

This section shows a robustness conducted at the CZ level with both OLS and 2SLS methods. As discussed earlier, endogeniety may not be a serious issue at the small geographical level of county, but it could cause considerable problem when it comes to CZ, which is significantly larger than a county. Therefore, it is reasonable to use a proper instrumental variable in analyzing CZ level data. As outlined in section 1.7.2, the instrumental variable strategy for the change in import exposure per worker measure ΔIPW aims at identifying the component of US import growth that is due to China's productivity improvement and trade cost reduction. The assumption underlying this strategy is that the common within-industry component of rising Chinese imports to the US and other developed countries is China's rising comparative advantage and falling trade barriers (Autor, et al. 2013). In addition, in order to identify (1.3), I use the cross term $\left(\Delta IPW_{o,i} * self\_emp_i\right)$ as an instrument for $\left(\Delta IPW_{US,i} * self\_emp_i\right)$. With these two instrumental variables[10], I can estimate (1.3) using 2SLS. The dependent variable Δy_i is calculated as the log value in 2007 minus the log value in 2000, so that the regression coefficients provide the percentage change from the initial year. For ease of interpretation, in all regressions of this paper the share of self-employment $self\_emp_i$ and the import shock $\Delta IPW_{US,i}$ are calculated as deviation from their median values.

In Table 1.7, column 2(a)~a(d) show the 2SLS results model (1.3) with robust standard errors clustered by state. In column 2(a) we estimate model (1.3) without control variables and state dummies. In column 2(b) state dummies are included for controlling regional omitted bias. Column 2(c) adds the four regional demographic and social control variables, and column (d) adds the lagged industrial structure control variables. The coefficients of $\Delta IPW_{US,i}$ in all settings are negative and statistically significant. This means CZs with higher import increases from China had less employment growth compared with CZs not experiencing such increases. More importantly, the coefficients of cross-term $(\Delta IPW_i * self\_emp_i)$ are statistically

10 In the regression of $\Delta IPW_{US,i}$ on its instrumental variable $\Delta IPW_{o,i}$, the F-statistic is 687.38 and R2=0.49; in the regression of the cross-term $\left(\Delta IPW_{US,i} * self\_emp_i\right)$ on its instrumental variable $\left(\Delta IPW_{o,i} * self\_emp_i\right)$, the F-statistic is 458.82 and R2=0.39. Thus we can statistically reject the weak instrument hypothesis for both.

significant and positive in all model settings. This indicates that for regions with higher shares of self-employment, the net effects of Chinese import shocks, expressed as $(\beta_1 + \beta_2 self\_emp_i)$, are smaller, which confirms our earlier proposition that in regions with higher shares of entrepreneurs/self-employment, the adverse impacts of trade shock on local labor market are dampened.

The instrumental strategy here is to use the contemporaneous changes of Chinese imports to other high-income countries ($\Delta IPW_{o,i}$) as IV for the Chinese import penetration to US local labor market ($\Delta IPW_{US,i}$). The reason for doing that is to avoid the possible reverse impacts of US internal economic shocks on import change (Autor et al., 2013). However, when it comes to the Commuting Zone level, it is also possible that an internal shock at the local labor market would have virtually no effect on the overall imports from China. Thus to what extend the endogeneity issue at the national level can be applied to the local level is still questionable, especially when we have controlled for the lagged industrial structure of CZs here in model 2(d). In fact, not all of recent similar studies about trade shock and local labor markets occupy themselves with some sort of endogeneity issue (like, for example, Kandilov (2009) and Kovak (2013)). Thus as an eclectic approach, we also estimate model 2(d) with OLS, and the results are reported in 2(e). We can see that the results do not fundamentally deviate from what we get in the 2SLS estimation 2(d), i.e. the cross-effect of trade penetration and self-employment rate is still significantly negative and with similar magnitude.

Table 1.7 Cross Effects of Self-employment and Import Shock on the US Commuting Zone Labor Markets (2000-2007)

DepVars: 100×ΔLog (Counts of Wage-and-Salary Employment)

	2SLS				OLS
	(a)	(b)	(c)	(d)	(e)
(ΔImport from China to the US)/worker, ΔIPWus,i	-2.81***	-1.55***	-1.63***	-0.98***	-0.98***
	(0.44)	(0.28)	(0.28)	(0.30)	(0.23)
Cross-term, (ΔIPWus,i*self_emp$_i$)	0.48***	0.35***	0.36***	0.31***	0.19***
	(0.11)	(0.09)	(0.08)	(0.07)	(0.06)
Share of self-employment in total employment	-0.17*	-0.30***	-0.35***	-0.41***	-0.48***
	(0.10)	(0.10)	(0.12)	(0.13)	(0.12)
Percentage of college educated population			0.25***	0.21***	0.21**
			(0.07)	(0.08)	(0.08)
Percentage of white people			0.14***	0.15***	0.16***
			(0.04)	(0.03)	(0.03)
Percentage of population age 20-29			-0.01	-0.04	-0.04
			(0.17)	(0.16)	(0.16)
Commuting zone population			-0.37	0.02	0.03
			(0.35)	(0.27)	(0.28)
Lagged industrial structure (1990)				Yes	Yes
State dummies		Yes	Yes	Yes	Yes
R^2	0.06	0.28	0.32	0.46	0.47

Notes: N = 709 Commuting Zones. Robust standard errors clustered by state are in parentheses. $\Delta IPW_{us,I}$ and self_emp$_i$ are calculated as deviation from their median values.
**** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
** Significant at the 10 percent level.*

Next, based on the results of Table 1.7 and the distribution of self-employment rates over CZs, we can retrieve the point estimates of the impacts of trade shocks over the spectrum of self-employment rates. Since in our regressions the share of self-employment is calculated as the deviation from its median value, the coefficient of $(\Delta IPW_{US,i})$ in Table 1.7 should be interpreted as its actual point estimate for a CZ with the median self-employment rate. In Table 1.8 we calculates the marginal impacts of a one thousand dollars' change in Chinese imports per worker on labor markets for CZs at the 25%, 50%, and 75% self-employment rate percentiles. Specifically, if we use the 2SLS regression results of table 2(d), then for a CZ with a self-employment rate at about the median value of all CZs in the US (8.14%), the impact of a one thousand dollars' import increase per worker on the employment growth is -0.98%. This impact for CZs at the 25% and the 75% percentiles of self-employment rates is −1.50% and −0.13% respectively. If we use the OLS results of model 2(e), $\Delta IPW_{us,i}$'s impacts become -1.30%, -0.98%, and -0.46% respectively for CZs at the 25%, 50%, and 75% percentile self-employment rates. These results suggest that entrepreneurial regions are more resistant to trade shocks. Please notice here that, the above discussions and figures are particularly about self-employment's roles in mitigating the adverse impacts of trade penetration, rather than a general estimation of the overall impacts of entrepreneurship on the general growth of local labor market. In fact, a complete prediction of entrepreneurs' long term consequences on regional economy is a complicated process, which involves many subtle effects like space issues, time dynamics, and indirect cross-effects with incumbent firms (Fritsch, 2013; J. Henderson & Weiler, 2009), and is beyond the scope of our study.

Table 1.8 Actual marginal impacts of $1,000's change in Chinese import per worker on employment growth for CZs with different self-employment rates (2000-2007)

	(a)	(b)
	Calculated from table 2(c)	Calculated from table 2(d)
At 25% percentile of self-employment rate	-2.24%	-1.50%
At 50% percentile of self-employment rate	-1.63%	-0.98%
At 75% percentile of self-employment rate	-0.64%	-0.13%

Source: Author calculations, based on 2SLS regression results of Table 2. The self-employment rate at the 25%, 50%, and 75% percentile of US Commuting zones are 6.45%, 8.14%, and 10.88% respectively.

2 Trade Shock and New Industry Entry: Regional Resilience from an Evolutionary Perspective

Summary

This article examines economic resilience against trade shocks from an evolutionary perspective, which focuses on a region's ability of attracting new industry entrants and developing new growth pathways. It is found that U.S. urban counties experiencing greater Chinese imports penetration are more likely to attract new industry entries. By bringing new growth opportunities to local economies, the trade shock-induced new industry entrants promote economic resilience. It is also found that regions with higher levels of entrepreneurship and/or industrial varieties are more capable of attracting new industries when facing trade shocks, and thus have higher adaptability.

Keywords: resilience, evolutionary economic geography, industry entry, trade shock

JEL classifications: L25, L60, R00, R10

2.1 Introduction

The impacts of globalization on regional economies have been widely studied in recent years. Although trade liberalization can increase welfare in general, the distribution of its benefits and costs is uneven among different regions, sectors, and labor groups (Bustcos, 2011; Krishna et al., 2012; Melitz, 2003). For high-income countries a notable transformation in the patterns of international trade during the past several decades has been the rapid growth of import competition from newly industrialized countries (Krugman, 2008). Many recent studies also suggest that import penetration from low-income countries can adversely influence local economies in the short run (Autor et al., 2013; Leichenko & Silva, 2004). In this background, economic resilience in the face of trade shocks has attracted increasing attention in researchers and policy practitioners. The main goal of this article is to study regional resilience against trade shocks from a new perspective of evolutionary economic geography.

Traditionally, the idea of resilience is usually based on an engineering or equilibrium concept in which resilience is reckoned as a passive response to external shocks or a recovery to the original status. Recent studies in Economic Geography, however, advocate an evolutionary approach to regional resilience, which emphasizes the capacity of an economy to reconfigure its economic structure and develop new growth pathways (Christopherson et al., 2010; Hassink, 2010; Simmie & Martin, 2010). Some scholars explicitly distinguish between these two approaches to resilience as *adaptation* and *adaptability*, respectively (Boschma, 2015; Pike et al., 2010). In this sense, this article aims to study the adaptability dimension of regional resilience, focusing on how a region can convert the adverse impacts of trade shocks into stimulus for developing new growth opportunities.

Trade liberalization reveals a country's comparative advantage in the global market scale, and the influence it brings to the economy is heterogeneous among different sectors. Import competitions from low-income countries act as structural shocks, and regions that are more capable of adjusting their own economic structures according to their comparative advantages can achieve better economic performance (Hanson & Slaughter, 2002; Liang & Goetz, 2016). Based on the factor reallocation effect caused by import competition, this paper develops a probability model of trade shock-induced new industry entry. Trade shocks may help to free regional production factors from declining sectors and then reallocate them to industries with better growth potential. Thus it is expected that regions experienced higher levels of import competition are more likely to attract new industry entries. This hypothesis is supported by data of U.S. urban counties and Chinese imports during 2000-2007. The emergence of new industries in a region can create diversified growth opportunities and also help to revive the local economy, which will further reshape economic geography (Hall & Preston, 1988; Marshall, 1987; Neffke et al,. 2011). Thus when facing trade shocks, the ability to attract new industries and to develop new growth pathways can contribute to regional resilience and long-term development.

Then another important question is, what can make a region *more* capable of attracting new industries when it is faced with trade shocks. Thus the model is extended to include interaction effects between trade shocks and some regional economic variables, so as to investigate how the actual effect of trade shock-induced new industry entry is influenced by these conditions. Specifically considered are regional characteristics of entrepreneurship and industrial varieties (related and unrelated varieties), which have been widely studied in recent evolutionary economic geography literature (e.g., Castaldi et al., 2015; Essletzbichler, 2015; Liang & Goetz, 2014). Empirical results show that both entrepreneurship and industrial varieties can enhance a region's ability to attract new industry entries when facing trade shocks. This means a higher level of entrepreneurial activities and/or a diversified industrial structure can help to make a region more capable of developing new growth opportunities and thus the economy is more resilient.

This paper, to the best of the author's knowledge, is the first one in the literature to analyze trade shock and resilience from an evolutionary perspective of economic geography. This study offers an effective method to conceptualize regional resilience as the ability of converting the adverse impacts of external shocks into new growth opportunities. It also empirically analyzes how this adaptability is influenced by regional characteristics like entrepreneurship and industrial varieties.

Next section discusses trade shock and factor reallocation effect, and proposes the empirical model. Section 2.3 describes data and variables, with the empirical results reported in Section 2.4. Section 2.5 extends the model to analyze the influences of regional conditions of entrepreneurship and industrial variety. Section 2.6 includes some further discussion, and Section 2.7 concludes the whole chapter.

2.2 Trade shock-induced new industry entry

Theories indicate that trade liberalization increases competition and encourages countries to specialize in the industries in which they have comparative advantages. In other words, trade will result in redistribution of resources among industries. In recent decades, researchers have studied this trade shock-induced reallocation effect at more detailed levels. Krugman (1980), Melitz (2003), and Melitz & Ottaviano (2008) incorporate firm level productivity heterogeneity into trade models and suggest that the impacts of trade penetration vary across firms of different productivity levels. Thus, when impacted by import competition, firms' chances of survival depend on their relative productivity. This leads to an intra-industry (between-firm) reallocation of factors (see Tybout (2003) for a review). More recent studies point out that this trade shock-induced reallocation effect exists not only at the intra-industry level but also at intra-firm level, i.e., multi-product firms confronted with trade shocks will reallocate resources to core products with the highest efficiencies (Bernard et al., 2010; Chen et al., 2009; Eckel & Neary, 2010; Iacovone & Javorcik, 2010; Mion & Zhu, 2013).

In this stream of literature, however, limited attention has been given to regional analysis. Few previous studies have investigated how trade shocks reallocate factors and resources within a region and stimulate new industry formations in a local economy. Some studies on trade liberalization and local labor markets have discussed trade shock-induced structural change in employment, which are more relevant to this article. In these studies, trade shocks influence regional economies through local industrial composition. Assuming imperfect factor mobility, the sectors that are relatively more penetrated by imports will be at a disadvantage and suffer higher losses compared with sectors that are not (Borjas & Ramey, 1995; Kovak, 2013; Leichenko & Silva, 2004; Topalova, 2010). Autor et al. (2013) use a general equilibrium model to investigate how the increasing Chinese import competition affects employment and wages in U.S. commuting zones. Based on their model, an increase in Chinese imports stimulates a reallocation of labor between traded and non-traded sectors as well as within traded sectors due to wage imbalance.

Therefore, the basic hypothesis of this study is that trade shock leads to a factor reallocation effect in a regional economy, then increases the probability of new industry formation. The direct impacts of import competition are basically negative, as it brings about wage cut and job losses to the local economy. But it can also help to unfreeze regional production factors, such as labor and land, from those declining sectors and make them available to new industries. As a result, *ceteris paribus*, regions with higher levels of trade shock are more likely to attract new industry entries. This hypothesis leads to the following empirical model about the entry of industry *i* in region *r*:

$$\begin{aligned} Probability\ of\ entry_{i,r} \\ &= Trade\ shock_r + regional\ control\ variables \\ &+ industry\ fixed\ effects_i \end{aligned}$$

or in a mathematical form of:

$$\boldsymbol{Prob}(Entry_{i,r}) = C + \beta * Trade\ shock_r + controls_r + \alpha_i + \epsilon_{i,r} \tag{2.1}$$

where α_i is industry dummies. In the theoretical appendix, a probability model is developed to show how trade shocks influence local factor prices, and then lead to an industry entry model like (2.1). The focus of this model is industry entry, so the industry *i* in (2.1) only refers to those that do not exist in the industrial portfolio of region *r* at the beginning period, and thus they have the potential to enter. The right hand side of the model means that after controlling for regional control variables and fixed effects of each industry, a higher level of trade shock can generally increase the probability that a region attracts new industry entrants. Next section will describe details about all the variables.

There are some important assumptions about this model. First, it is assumed that factors are imperfectly mobile between regions, so as to allow the factor reallocation effect occur within a regional economy. Thus the analysis in this article is short to median-run in nature. Second, the industry fixed effect are used to control for industry specific development trend that is common in the country-wide during this period. It may include two parts of effects. One is the original long-term development trend of a sector in the US. For example, a matured industry, such as winery, is less likely to spread out to new locations than some other emerging business such as software engineering. The other part is trade induced influences on each industry, which includes not only the direct impacts of import competition but also the supply-chain effects[11].

11 Imports of intermediate inputs purchased by US firms increases the variety of inputs to which US producers have access, and it may raise their productivity.

2.3 Variables and data

2.3.1 Portfolio membership and new industry entry

In order to define and empirically measure industry entry, i.e., the dependent variable of (2.1), the method here follows the industrial portfolio approach of Neffke, et al. (2011). If an industry *i* has non-zero employment in region *r* in a specific year *t*, it is said that *i* exists in the industrial portfolio of region *r* at time *t*, or:

$$Portfolio\ (i,r,t) = \begin{cases} 1, & Employment_{i,r,t} > 0 \\ 0, & otherwise \end{cases}$$

If the employment of industry *i* in region *r* is null at time *t0* and is non-zero at time *t1*, then there is an observed industry entry, or:

$$Entry\ (i,r,t0 \longrightarrow t1) = \begin{cases} 1, & Portfolio\ (i,r,t0) = 0\ and\ Portfolio\ (i,r,t1) = 1 \\ 0, & Portfolio\ (i,r,t0) = 0\ and\ Portfolio\ (i,r,t1) = 0 \\ NA, & Portfolio\ (i,r,t0) = 1 \end{cases}$$

For the sake of brevity, the time argument (*t0⟶t1*) is omitted in the expression of *Entry* hereafter. Note that entry is a region-industry specific variable, and it has a valid observation only when *Portfolio(i,r,t0)=0*.[12] Data for calculating *Portfolio* and *Entry* are drawn from the U.S. Census County Business Patten (CBP), which provides the annual county data of employment and establishment by detailed industry. In this study, industry is examined at the 5-digit NAICS level of manufacturing sectors, which yields 184 industries. There are altogether 1087 metro counties in the dataset. Thus, the number of all the possible region-industry observations is 184*1087=200008, about three-fourths of which have zero employment in the

12 Clearly, it makes no sense to define “entry” for industries that have already existed in a region's portfolio at the initial period.

beginning year 2000 (140396 observations). The descriptives of all observations are shown in Table 2.1.

Table 2.1 Summaries of regional-industry entry (2000-2007)

<table>
<tr><th>All r-i combinations</th><th>Portfolio(i,r,2000)</th><th>Portfolio(i,r,2007)</th><th>Entry(i,r)</th><th>% of Entry(i,r)</th></tr>
<tr><td rowspan="3">184*1087=200008</td><td rowspan="2">0; N=140396</td><td>1</td><td>1; N= 11674</td><td>8.32</td></tr>
<tr><td>0</td><td>0;
N=128722</td><td>91.68</td></tr>
<tr><td>1; N= 59612</td><td colspan="3">NA</td></tr>
</table>

Note: *r* indicates a US metro county and *i* indicates a 5-digit NAICS manufacturing industry.

Data Source: CBP (2000, 2007)

2.3.2 Regional trade shock

Trade data in this study focuses on the increase in Chinese imports from 2000 to 2007, a period with greater increase in Chinese imports than ever before and before the financial crisis. Two reasons make this data ideal for the research here. First, the increase in Chinese imports accounted for most of the U.S. import increases from low income countries during this period; second, the trade advantage of Chinese manufacturers was largely due to increased productivity and/or lowered trade barriers, which were likely to be exogenous to local U.S. economies at the county level (Liang & Goetz, 2015), allowing for greater estimation efficiency.

U.S. county-level import statistics are not available from any public database. Thus, a measure of counties' trade exposure need to be indirectly derived based on local industry specialization, an approach widely used in recently studies (Edmonds, et al., 2010; Kandilov, 2009; Kovak, 2013; Topalova, 2010). Specifically, the exposure to trade shock in a region is measured by change in Imports Per Worker (ΔIPW hereafter), calculated as:

$$\Delta IPW_r = \frac{1}{L_r}\sum_i \frac{L_{i,r}}{L_{i,US}}\Delta M_i \qquad (2.2)$$

where ΔM_i is the change in Chinese imports (in thousand$) in sector i for the whole U.S. during this period; $L_{i,r}$ is employment of sector *i* in county *r*; $L_{i,US}$ is employment of sector *i* in the U.S.; and L_r is total manufacturing employment in county *r*. Therefore, ΔIPW_r measures the import shock per worker in county *r* during this period (in thousand-$/worker). A greater ΔIPW_r means higher import competition. Given the time frame of analysis is 2000-2007, the import change ΔM_i is the difference from 2000 to 2007, and all employment variables are initial year (2000) values.

Autor et. al. (2013) point out that economic performances such as wage, employment, and work participation in a region are negatively proportional to the trade shock measure as in (2.2). So ΔIPW_r can be used as a proxy for the economic turbulences of import penetration. Then the core independent variable of model (2.1), *Trade shocks*, will be substituted with ΔIPW_r. In (2.2), data of Chinese imports M_i are from the International Trade Statistics database of U.S. Census Bureau[13]; the three labor variables $L_{i,r}$, $L_{i,US}$, and L_r for initial- and end-years come from CBP 2000.

2.3.3 Local input-output linkage

Local input-output linkages need to be appropriately controlled for in the model, as they strongly correlate with the evolvement of regional industry structure. Development of an industry depends on exchanges of tangible and intangible factors with other sectors, and thus

13 http://www.census.gov/foreign-trade/data/

the supports from related, pre-existing sectors in a region is essential for the emergence of new firms and new industries (Glaeser & Kerr, 2009; Neffke et al., 2011). The intensity of local input-output linkage between an industry and the incumbent firms of a region provides a relevant measure for the closeness of supply chain and technology similarity between this industry and the existing sectors.

The input (*INP*) and output (*OUT*) linkages of a focal industry with the incumbent sectors in a region are measured as (2.3) and (2.4), respectively. Subscripts *i* and *k* index industries at the 5-digit level, where *i* is a focal industry and *k* refers to all incumbent industries in a region. $Input\_share_{i \leftarrow k}$ in (2.3) is the share of intermediate input values that *i* obtains from *k* in the total intermediate input purchase values of *i*, and $Output\_share_{i \rightarrow k}$ in (2.4) is the share of *k*'s purchase from *i* in *i*'s total output values. $ES_{k,r}$ is employment share of sector *k* in region r. $INP_{i,r}$ and $OUT_{i,r}$ are calculated as the initial year-2000 values with employment data from CBP 2000, and $Input\_share_{i \leftarrow k}$ and $Output\_share_{i \rightarrow k}$ are calculated based on 1997 U.S. Benchmark Input-Output Data[14].

$$INP_{i,r} = \sum_k ES_{k,r} * Input\_share_{i \leftarrow k} \tag{2.3}$$

$$OUT_{i,r} = \sum_k ES_{k,r} * Output\_share_{i \rightarrow k} \tag{2.4}$$

$INP_{i,r}$ ($OUT_{i,r}$) measures the abundance of input suppliers (output markets) in region *r* for industry *i*. Proximity to and suppliers and demanders reduces shipping costs and makes a region

14 See the website of U.S. Bureau of Economic Analysis (BEA) at http://www.bea.gov/industry/io_benchmark.htm for data source and other information about the US Benchmark Input-output Table.

more attractive to potential entrants. Input-output linkage and the incurred difference in transportation costs are widely studied in New Economic Geography (NEG) literature and are reckoned as core agglomerative forces (Fujita et al., 2001, 1999; Krugman, 1991). The literature also suggests that geographic proximity to upstream and downstream firms can enhance innovation and productivity by increasing a firm's awareness of what products are preferred by customers and what novel inputs are available (Porter, 1990).

2.4 Empirical results

Besides the input and output linkages described above, the regional control variables also include several local demographic factors: population, share of white people, and age composition of local population. These data are obtained from the U.S. Census 2000 database[15]. Descriptive statistics of all independent variables are shown in Table 2.2. For ease of interpretation, in all following regressions the trade shock *ΔIPW* and input-output linkages (*INP* and *OUT*) are normalized with median values equal to 0 and standard deviations equal to 1.

15 http://www.census.gov/main/www/cen2000.html

Table 2.2 Descriptive statistics of independent variables (US metro counties 2000)

	M.	**S.D.**
ΔIPW_r **(thousand $/worker)**	12.35	14.70
INP	1.11 E-3	5.02 E-3
OUT	0.67 E-3	5.11 E-3
Population density (/Sq. Mile)	613.0	2783.8
Percentage of white people (%)	82.68	15.03
Percentage of age under 18 (%)	25.80	3.02
Percentage of age 40-64 (%)	30.79	2.91
Percentage of age above 65 (%)	12.46	3.40

Note: Import change data are for 2000-2007.
Data source: US International Trade Statistics of US Census Bureau; US Census 2000; CBP 2000.

Regression results of model (2.1) are reported in Table 2.3. In columns (a) and (b) the model is estimated using OLS with robust standard errors, and in (c) and (d) using Probit method. The coefficients of trade shock ΔIPW are significantly positive in all columns, suggesting that a higher level of trade shock makes a regional economy more likely to attract new industry entries. These results confirm the prediction that the probability of new industry entry in a region is positively correlated with trade shock. Further analysis on the marginal effects based on the results of Table 2.3(d) suggests that compared with regions at the median value of trade shock, a one standard deviation's difference in ΔIPW_r increases the possibility of a new industry entry by 0.3%. This is a noticeable increment considering that there are altogether 184 industries studied in the data.

Table 2.3 Trade shock-induced new industry entry in metro counties (2000-2007)

	OLS		Probit	
	(a)	(b)	(c)	(d)
ΔIPW ΔIPW_r	3.31 E-3 ***	2.38 E-3 ***	0.023 ***	0.017 ***
	(6.75 E-3)	(0.67 E-3)	(0.005)	(0.005)
INP		1.76E-3 ***		0.014 ***
		(0.59 E-3)		(0.005)
OUT		2.31 E-3 ***		0.019 ***
		(0.68 E-3)		(0.004)
Demographic controls		Yes		Yes
Industry fixed effects	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes

Notes: N=140396 region-industries. *ΔIPW*, *INP*, and *OUT* are normalized with median values equal to 0 and S.D. equal to 1. Robust standard errors are reported in parenthesis for OLS. Level of statistical significance: * p<0.10; ** p<0.05; *** p<0.01.

2.5 Regional variations

The above results reveal a process of creative destruction in regional economies under trade shock. Although greater import competition brings about short-term economic loss, the lowered wage and factor prices increase the possibility of new industry entries, which in turn provide diversified growth opportunities that may revive the local economy. Such trade shock-induced new industries can also help to reconfigure local economic structure and make it more adaptable to foreign trade. Therefore, this effect of trade shock-induced new industry entry can be interpreted as an indicator of regional resilience. A higher value of the coefficient β in (2.1) is associated with greater resilience because when facing the same level of common trade shock, adaptable regions are more likely to attract new industries.

Model (2.1) assumes that coefficient β, i.e., the marginal impact of trade shock on the probability of new industry entry, is identical among all counties. This, however, rules out the possibility that regions have different abilities in converting trade shocks into opportunities for new industry entry. Thus, this assumption is relaxed in this section, and the regional variations in the trade shock-induced new industry entry is investigated. Specifically, suppose that economic resilience is influenced by some regional condition X_r, then model (2.1) becomes:

$$\boldsymbol{Prob}(Entry_{i,r}) = C + \beta_1 \Delta IPW_r + \beta_2 X_r + \beta_3(\Delta IPW_r * X_r) + \alpha_i + controls_i + \epsilon_{i,r} \tag{2.5}$$

where the actual coefficient of ΔIPW_r on the probability of new industry entry is $(\beta_1 + \beta_3 X_r)$ instead of β as in (2.1). Thus, the regression results of β_3 will reveal how X_r influences the ability of region *r* to attract new industries when the local economy is faced with trade shock.

2.5.1 Entrepreneurship

Entrepreneurship has been believed to be associated with creative destruction and economic renovation from early studies (Schumpeter, 1934). Entrepreneurs may play different roles in the economy. Some may merely fill "market gaps" (Leibenstein, 1968) or engage in arbitrage (Kirzner, 1997), both of which target market niches in local economies, whereas other entrepreneurs might be classic Schumpeterian innovators who aim to create new businesses patterns. A common characteristics of these different types of entrepreneurs is that they are all likely to operate businesses that differ from those of the dominant incumbent firms, which may finally lead to the formation of new and diversified industries in the local economy. More recent studies focus on entrepreneurial activities' innovation nature, which can bring about novel products and stimulate a local economy to better adapt to uncertain conditions in a market (Acs & Szerb, 2007; Acs & Varga, 2005). Recent research also suggests that entrepreneurs can accelerate an economy's structural evolution by introducing greater competitions into the market and absorbing the surplus labor force from shrinking sectors (Fritsch, 2013; Gries & Naudé, 2010).

The measure for entrepreneurship is based on industry-weighted firm entry rates (Fritsch, 1997; Johnson, 2004; Renski, 2012). Firm entry rate is defined as the number of entrants divided by the number of incumbent firms in an industry. Supposing that the average firm entry rate of industry *i* at the national level is $\bar{E}_i$, its actual entry rate in region *r* is $E_{i,r}$, and $s_{i,r}$ is the share of industry *i* in total firm numbers of region *r*, then the regional entrepreneurship level is calculated as:

$$ENT_r = \frac{\sum_i s_{i,r} * E_{i,r}}{\sum_i s_{i,r} * \bar{E}_i} \tag{2.6}$$

where the nominator is the actual new firm formation rate of region *r*, and the denominator is an expected regional firm entry rate assuming every industry in the region resembles its national average entry rate. A higher level of ENT_r indicates greater regional entrepreneurial activity. Compared with other entrepreneurship measures, such as the actual firm entry rate, the advantage of (2.6) is that it accounts for the influence of regional industry mix. In order to avoid reverse causality, (2.6) is calculated with 4-digit SIC manufacturing sector data averaged from 1990 to 1994, roughly ten years' lag from the main study period (2000-2007). Regional industry shares $s_{i,r}$ are drawn from CBP (1990-1994), and sectoral firm entry data of counties are drawn from the U.S. Census' Business Dynamics Statistics (BDS)[16].

ENT_r is then substituted for X_r into model (2.5), and the regression results are shown in Table 4(a). The coefficient of the cross-term $ENT_r * \Delta IPW_r$ is significantly positive, indicating that entrepreneurship can promote trade shock-induced new industry entry. More specifically, in regions with greater entrepreneurial activity, the same level of trade penetration results in a higher probability of new industry entry.

2.5.2 Industrial varieties

The relationship between agglomeration and economic growth has been widely debated since the seminal work of Glaeser, et al. (1992). Following Jacobs (1969), one perspective of agglomeration economies is that the variety or diversity of regional industries can contribute to local economic development and resilience. It is suggested that industrial variety can help firms to recombine different forms of knowledge and ideas, leading to more innovations. As a result, in a diversified economic structure, different industries learn from each other and benefit from knowledge spillovers. Some scholars argue, however, that such diversity-related externalities are too general and need to be refined to be more specific (Porter, 2003). Thus, after Frenken, et al. (2007) distinguished between *related variety* and *unrelated variety*, these two concepts have been widely applied (e.g., Boschma & Iammarino, 2009; Boschma et al., 2012; Hartog et al., 2012; Oort et al., 2014; Saviotti & Frenken, 2008; Wixe & Andersson,

16 The BDS website (http://www.census.gov/ces/dataproducts/bds/data.html) provides firm entry and exit data for different industries at the national and state level. County data are obtained by special request.

2013).

Based on previous literature (Boschma, 2005; Frenken et al., 2007; Nooteboom, 2000), *related variety*, which measures the diversity of related industries, is associated with the potential gains of inter-sectoral knowledge spillovers and therefore contributes to gains in productivity. *Unrelated variety*, on the other hand, which measures the diversity of unrelated industries, can encourage the recombination of different ideas and incubate novel business ideas. This paper incorporates related variety and unrelated variety, respectively, into model (2.5) as the regional condition X_r and tests their impacts on regional adaptability. As in Bishop & Gripaios (2010) and Frenken et al. (2007), related variety (*RV*) at a two-digit NAICS sector level in a region is calculated using the following entropy method:

$$RV_{j,r} = \sum_{i \in I_j} \frac{emp_{r,i}}{emp_{r,j}} log\left(\frac{emp_{r,j}}{emp_{r,i}}\right) \tag{2.7}$$

where *emp* is the number of employed, *r* is a county, *j* is a 2-digit NAICS sector, and I_j is the set of all the industries at a more disaggregated level (5-digit NAICS sectors, which are denoted with subscript-*i*) that fall exclusively under the 2-digit sector *j*. Industries that belong to the same broader industry category are deemed as "related" to one another. For a 2-digit industry *j*, if its employment is distributed more evenly in the sectors of its disaggregated level, according to (2.7), it has a greater value of related variety. On the other hand, unrelated variety (*U*V) is calculated as the entropy diversity between the 14 two-digit NAICS sectors in a county, as in (2.8), where $emp_{r,j}$ is employment of the *j*-th two-digit sector in region *r*, and emp_r is the total employment of r. A higher value of *UV* means a greater variety of unrelated sectors.[17]

$$UV_r = \sum_{i=1:14} \frac{emp_{r,j}}{emp_r} log(\frac{emp_r}{emp_{r,j}}) \tag{2.8}$$

To avoid reverse causality, *RV* and *UV* are calculated as the initial year (2000) values, and all the employment data in (2.7) and (2.8) are from CBP 2000. Substituting *RV* and *UV* for *X* into model (2.5), the empirical results are shown in Table 2.4, column (b)~(d). Location quotients of manufacturing employment (LQM) is also included to control for the clustering effect of manufacturing sector in each region. In column (b) and (c) of Table 4, impacts of $RV_{j,r}$ and UV_r are analyzed respectively, showing that their cross-effects with the trade shock are both positive and statistically significant. In column (d), where $RV_{j,r}$ and UV_r are both included in the model, the two cross-terms are still positive, but $RV_{j,r}*\Delta IPW_r$ is no longer significantly different from zero. These results suggest that industrial varieties can generally enhance the trade shock-induced new industry entry effect in an urban county, and the influence of unrelated variety is stronger and more significant than related variety.

17 Note that the RV as in (7) is calculated at the 2-digit level for each region, whereas the UV as in (8) is at the region level. Thus, when incorporating each of them into model (5), the 5-digit industries belonging to a common 2-digit sector in a region have the same value of RV; and all 5-digit industries in a region have the same UV value.

Table 2.4 Cross-effects of trade shock and entrepreneurship/industrial variety on industry entry

	(a)	(b)	(c)	(d)
ΔIPW_r	0.017 ***	0.021 ***	0.018 ***	0.021 ***
	(0.0.005)	(0.006)	(0.005)	(0.006)
ENT_r	0.021 ***			
	(0.006)			
$ENT_r*\Delta IPW_r$	0.018 ***			
	(0.005)			
$RV_{j,r}$		0.523 ***		0.427 ***
		(0.008)		(0.009)
$RV_{j,r}*\Delta IPW_r$		0.014 **		0.005
		(0.007)		(0.008)
UV_r			0.419 ***	0.193 ***
			(0.009)	(0.010)
$UV_r*\Delta IPW_r$			0.021 ***	0.017 **
			(0.007)	(0.008)
INP	0.014 ***	0.030 ***	0.027 ***	0.032 ***
	(0.005)	(0.005)	(0.005)	(0.005)
OUT	0.019 ***	0.033 ***	0.031 ***	0.035***
	(0.004)	(0.004)	(0.004)	(0.004)
LQM		-0.001	0.016 ***	0.012 ***
		(0.004)	(0.004)	(0.004)
Demographic controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes

Note: N=140396 region-industries. Variables of trade shock (*ΔIPWr*), regional conditions (ENT_r, $RV_{j,r}$, UV_r), and control variables for input-output linkages are normalized with median values equal to 0 and standard deviations equal to 1.

Level of statistical significance: * p<0.10; ** p<0.05; *** p<0.01.

2.5.3 Actual marginal impact of trade shock on the probability of new industry entry

Figure 2.1 shows how the actual marginal probability of trade shock on industry entry changes with variable regional conditions. These marginal effects are calculated by applying the regression results of Table 4 to the probability distribution function of the Probit model. As Figure 1 shows, the actual effect of trade shock-induced new industry entry is significantly influenced by local economic conditions. The interaction effects of *ENT*, *RV*, and *UV* with ΔIPW_r are all positive, so higher levels of entrepreneurship or industrial varieties can make a region faced with trade shock more attractive to new industries.

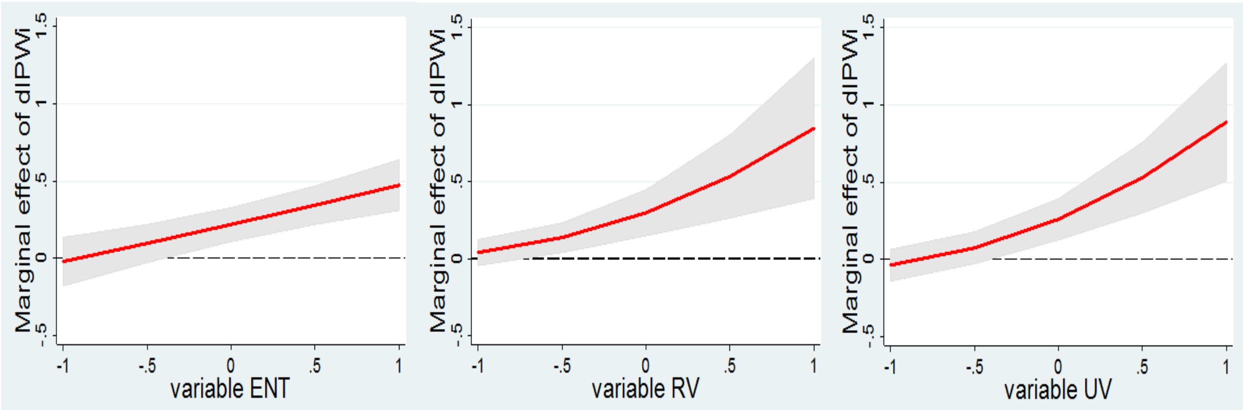

Figure 2.1 Variable regional conditions and the actual marginal impact of trade shock on the probability of new industry entry

Note: Calculated from Table 4(a), (b), (c), respectively. Shaded areas show 90% confidence intervals. For ease of comparison, X- and Y-axes are scaled with the same ranges, respectively. Regional condition variables are normalized, and thus each X-axis' scale corresponds to the variable's standard deviation. Y-axes are the actual marginal probability impacts of trade shock ΔIPW_i *on new industry entry, measured in %.*

Apparently, the interaction term of model (2.5) can also be interpreted from the other end, i.e., how trade shock ΔIPW_r can affect the marginal impacts of local conditions $X_{i,r}$ on new industry entry. Based on the results of Table 4, the influence of trade shock ΔIPW_r on the marginal impacts of regional conditions (X_{ir}) are relatively small compared with the standalone effects of X_r, and, therefore, in practice regional conditions of entrepreneurship and industrial variety are still positively associated with new industry entry.

2.6 Discussions

This article focuses on the adaptability of urban areas, so the empirical work is conducted at the U.S. metro county level. As an informative comparison, however, all the above models are also regressed with data drawn from U.S. rural counties and Chinese imports for the same period[18]. The results suggest that for non-metro counties the coefficient β in model (2.1) is still significantly positive, although with a smaller magnitude relative to metro counties. That means the effect of trade shock-induced new industry entry also exists in rural areas. For model (2.5), however, the non-metro regression results of the interaction effects do not neatly match those of metro counties and are not statistically different from zero. This might be explained by the fact that all the regional economic conditions investigated in Section 2.5 are generally related with the agglomeration effect, which tends to be more pronounced in urban areas (Glaeser, et al., 1992; Henderson, et al., 1995; Partridge, et al., 2009), muting their interaction effects in non-metro counties.

In order to test the robustness of the empirical results at different geographic levels of urban areas, the empirical work is repeated with Metropolitan Statistical Area (MSA) data for sensitivity analysis. These results[19] suggest that the conclusions drawn from the metro-county level analysis still hold. This paper focuses on county-level analysis rather than analysis at a

18 Detailed results are available upon request.
19 Available upon request.

functional geographic unit-level such as MSA primarily because in the U.S., county is the smallest administrative level with an independent government, and thus the results have more relevant policy implications.

Before concluding, some limitations and conditions of this study bear addressing. The following issues should be considered when generalizing the findings of this work to other circumstances, but they are also potential topics for future research. First, this study focuses on trade shock-induced new industry entry. Industry exit and/or firm closure caused by trade shock is not investigated despite its important role in the evolution of industry structure and long-term economic performance. Second, the empirical work is based on a probability model with a binary dependent variable of industry entry, so other economic indicators of any new entrant, such as employment and productivity, are not considered in this framework. Third, a core assumption of the model is imperfect factor mobility, and the time span of the empirical data (2000-2007) also limits the relevance of the study's conclusions in a long-run framework where factor mobility might be more mobile.[20] As a result, this study's conceptual and empirical work are limited to the short and medium run. Fourth, import penetration of Chinese imports over the research period was a special case of trade shock, which represented competition from low-wage manufacturers on developed countries. More empirical evidence is therefore needed before applying the conclusions of this study to other types of economic shocks.

20 The influences of 2007-2008 financial crisis make data for the several years subsequent to the period under study inappropriate for trade shock analysis, as it would be difficult to distinguish between the influences of trade shock and financial crisis shock; however, were data for a longer period to become available, in which the disturbances caused by the financial crisis can be smoothed out, relevant long-run studies might be feasible.

2.7 Concluding remarks

This article examines regional resilience against trade shock from an evolutionary perspective. A probability model of industry entry is used to investigate the qualitative changes in industrial structure of a region's economy. The model suggests that although the direct impact of import competition may be adverse on local economy (i.e., employment, wage, and output), it also leads to a factor reallocation effect that provides opportunities for the emergence of new industries. This prediction is confirmed in an empirical analysis which is based on data drawn from U.S. metro counties and Chinese import. Specifically, after controlling for industry-fixed effects, regions subject to higher levels of trade shock are more likely to attract new industries. From the perspective of evolutionary economic geography and the concept of creative destruction, these trade shock-induced new industry entrants offer new growth opportunities which may counteract the economic loss caused by import competition and contribute to the revival of the local economy, strengthening regional resilience. The model is then extended to analyze how this trade shock-induced new industry entry effect is influenced by regional conditions. By incorporating interacting terms of trade shock and some regional economic variables into the model, it is found that higher levels of entrepreneurship or industrial varieties can generally enhance a region's ability to attract new industries when faced with trade shock. This means entrepreneurial activities and industrial varieties make a regional economy more resilient.

There is a tendency in recent economic geography literature to advocate for an evolutionary perspective when discussing resilience. Researchers suggest that adaptability, i.e., the ability to reconfigure economic structure and develop new growth paths, is an important dimension of regional resilience. To the best of the author's knowledge, this article is the first practical application using this adaptability approach in an empirically study of regional resilience against trade shocks. This study complements the evolutionary-based literature about resilience and also provides new methods to conceptualize and empirically analyze the notion of adaptability in a regional economy. Another important finding of this article is that entrepreneurship and industrial variety can both contribute to a region's economic resilience. Entrepreneurial regions are usually more capable of adjusting their labor markets and economic structure, allowing them effectively adapt to external shocks. A diversified industrial structure provides ample opportunities for the creating of new ideas and business patterns, which are essential for the emergence of new industries and growth paths. Thus it is advisable for policy makers and practitioners to consider coordinating policies and strategies about regional resilience, entrepreneurship, and industry diversification, so as to achieve better policy efficiencies.

2.8 Appendix: A probability model of Trade shock-induced new industry entry

This section proposes a probability model to embody the factor reallocation effect and specify the empirical model. It is assumed that L_i is the total labor force in region *i*, there is no migration, and at time *t0* the equilibrium wage in region *r* is W_r. Each industry *i* in region *r* (whether *i* exists in the portfolio of *r* or not) has a "breaking point" wage level $W^*_{i,r}$, which means if the actual wage is lower than this breaking point, then the industry is earning positive profit. Thus, if we assume that labor productivities are identical, then industry *i* should exist in region *r* if $W_r < W^*_{i,r}$, which yields a decision making model:

$$Portfolio\ (i,r,t0) = 1 \quad if \quad W^*_{i,r} - W_r + v_{i,r} > 0 \tag{2.A1}$$

where $v_{i,r}$ is a decision error term that represents all the non-wage factors that influence the existence of industry *i* in region *r*.[21] Trade shocks happen during $t0 \longrightarrow t1$ and cause W_r and $W^*_{i,r}$ to change in the ratios of $\widehat{W}_r$ and $\widehat{W}^*_{i,r}$, respectively (*hat* means percentage change). Thus, at time *t1*, the portfolio condition is:

$$Portfolio\ (i,r,t1) = 1 \quad if \quad W^*_{i,r}\left(1 + \widehat{W}^*_{i,r}\right) - W_r\left(1 + \widehat{W}_r\right) + u_{i,r} > 0 \tag{2.A2}$$

where $u_{i,r}$ is a new decision error term for this period. For region-industry observations with *Portfolio (i,r,t0) = 0*, rearranging (2.A2) yields:

$$Entry_{i,r} = 1 \quad if \quad W^*_{i,r} * \widehat{W}^*_{i,r} - W_r * \widehat{W}_r + (W^*_{i,r} - W_r) + u_{i,r} > 0 \tag{2.A3}$$

It is further assumed that at *t0* (before the trade shock occurs), the country's labor market

21 Notice that in this model we can also interpret labor Li and wage W in a more general way, i.e., Li refers to all the imperfectly mobile factors in a local economy, such as land, natural advantage, and resources, and W is a composite rent of them. Thus, the decision error term represents all the influences other than Li.

is in a long-term equilibrium, so that there are no systematic variations in W_r and $W_{i,r}^*$ for different regions, and thus they are replaced by a constant and an industry-fixed effect, respectively. Trade shock comes from outside the country and is industry specific, so $\widehat{W}_{i,r}^*$ is substituted with $\widehat{W}_i^*$. After this substitution, model (2.A3) becomes the following probability model (the distribution function $\Phi(\bullet)$ on the right hand side is omitted for brevity):

$$\textbf{\textit{Prob}}(Entry_{i,r}=1) = C + \theta_1 * \widehat{W}_r + \theta_2 * \widehat{W}_i^* + \eta_i + \epsilon_{i,r} \tag{2.A4}$$

where θ_1 and θ_2 are coefficients to be decided and η_i is industry-fixed effect. In (2.A4), the industry wage change $\widehat{W}_i^*$ is not identifiable due to the presence of η_i, so model (2.A4) becomes:

$$\textbf{\textit{Prob}}(Entry_{i,r}=1) = C + \theta_1 * \widehat{W}_r + \alpha_i + \epsilon_{i,r} \tag{2.A5}$$

where the new industry-fixed effect α_i sums $\widehat{W}_i$ and η_i. Using model (2.A5) and its earlier form (A3), the coefficient θ_1 is expected to be negative because a lower wage level can increase the (potential) profit of an industry and increase the possibility of new industry entrants. This also means that, after controlling for industry-fixed effect, trade shock-induced wage drop in a region should correlate positively with the possibility of new industry entries.

Given that the direct impacts of imports penetration on local labor markets are negative,

$\widehat{W}_i$ should be negatively correlated with regional trade shocks. Thus (2.A5) is written as (2.A6), where some control variables of local demographic conditions, $controls_r$, are also included. The coefficient of trade shock β is expected to be positive, meaning that increased Chinese imports stimulate the local economy to attract new industries. The specific form of regional trade shock is described in *section 2.3.2*.

$$\boldsymbol{Prob}(Entry_{i,r}) = C + \beta * Trade\ shock_r + \alpha_i + controls_r + \epsilon_{i,r} \tag{2.A6}$$

3 Related variety and sector employment growth in US commuting zones

Summary

In recent studies, researchers have argued that related variety is associated with inter-industry knowledge spillovers and economic growth. In this paper we investigate the impacts of related variety on sector employment growth at the US Commuting Zone (CZ) level with controls for other agglomeration effects, especially local input-output linkages. And we focus on how the effects of related variety vary among different sectors. Our results suggest that, first, related variety is more important in manufacturing sectors, especially in technology intensive industries. Second, sectors with higher levels of agglomeration are more likely to benefit from related variety, and the impacts of related variety on growth is greater in specialized CZ-industries. Third, related variety is associated with employment growth only for CZ-industries with relatively low to median growth levels. These results suggest the roles of regional variety in contributing to growth are principally sector-based, and significantly depend on region-industry specific conditions.

Keywords: Related Variety; Sector Growth; Knowledge Spillover; Input-output Linkage

JEL: D62 O18 R11 R12

3.1 Introduction

The relationship between agglomeration and economic growth has been widely debated since the seminal work of Glaeser et al. (1992). One perspective of agglomeration economies, following Jacobs (1969), is that regional variety or diversity of industries is an important factor for economic growth. It is suggested that regional variety can help local firms to recombine different forms of knowledge and ideas, leading to more innovations. As a result, in a diversified economic structure, different industries better learn from each other and benefit from knowledge spillovers. Some scholars suggest, however, that this argument of Jacobs Externalities is still too general, and needs to be refined and made more specific (Porter, 2003). After Frenken et al. (2007) made the important distinction between related variety and unrelated variety, these two concepts, especially the related variety, have been widely applied in recent literature studying inter-sectoral knowledge spillovers. And a number of recent empirical studies show that related variety contributes to the development of regional economies (e.g., Boschma & Iammarino, 2009; Boschma et al., 2012; Hartog et al., 2012; Oort et al., 2014; Saviotti & Frenken, 2008; Wixe & Andersson, 2013; among others) And now the concept of related variety has been widely incorporated into policy debates of regional economies (Asheim et al., 2011; Boschma & Frenken, 2011; Karlsen et al., 2011; Pessoa, 2014).

Although much of previous work has studied related variety at the regional level, it has also been suggested that the impacts of agglomerations and spillovers are primarily sector specific (Porter, 1998, 2000), and that they depend on key industrial characteristics such as technological intensity, production life cycle, etc. (Hartog et al., 2012; Neffke et al., 2011).

Bishop & Gripaios (2010) investigate the impacts of spatial externalities and relatedness on sectors of Great Britain and find remarkable heterogeneity in the impacts of related variety on different sectors. However, there is still limited literature about what conditions at the industrial level may influence the roles of related variety on economic growth, or, under what circumstances a sector will benefit more from knowledge spillovers measured by related variety. In this research, we explicitly address these questions by studying the employment growth of two-digit NAICS sectors in the US Commuting Zones (CZ or CZs thereafter). Our results suggest that the types of industry, technology intensity, agglomeration and specialization level, and conditional growth level are the factors that influence the relationship between related variety and sector growth. Another key feature of this paper is that we control for the impacts of local input-output linkages in our model. The intensity of local input-output linkages is closely correlated with related variety but it contributes to economic growth in a different way. Previous studies mostly overlooked this correlation so the effects of related variety and knowledge spillovers on growth may be over-estimated. Thus we design and include a proxy variable for the local input-output linkages in our model, in order to obtain more accurate estimations for the values of related variety.

The plan of this paper is as follows. Section 3.2 reviews the literature about regional variety, knowledge spillovers, and industry growth. Section 3.3 introduces the data and variables used in our model. Section 3.4 describes the correlation between local input-output linkage and related variety, and introduces our method to address the resulting problems. Then the following section presents the empirical results, which include OLS and quantile regression. Section 6 concludes.

3.2 Related variety, technology spillovers, and sector employment growth

Recent approaches to regional growth have emphasized the importance of industrial structure and its impacts on knowledge spillovers. Scholars have realized the agglomeration of economic activities is an especially important determinant of growth and can strongly affect economic geography, as the manner in which firms co-agglomerate significantly influences their learning and cross-fertilization (Ellison et al., 2010; Frenken et al., 2014; Glaeser et al., 1992). As an important effect of agglomeration economics, regional variety or diversity is widely studied in the recent decades.

In the early stage of this literature, the debate was about "specialization or diversity", i.e., whether the knowledge spillovers happen principally between firms of the same sector, or between firms of different sectors (Glaeser et al., 1992). The former argument finds its root in the MAR (Marshall--Arrow--Romer) externality, which is also known as the Marshall (1920) trinity, i.e., firms located close to other firms of the same sector can benefit from specialized input-output linkages, shared labor pool, and technology spillovers. The latter favors diversity and is usually traced back to the Jacobs externality (Jacobs, 1969), which claims that a diversified economic structure can recombine ideas and incubate innovations and technology breakthroughs. Both of these ideas have been widely studied and abundant empirical evidence has been found. However, more comprehensive reviews and meta-analysis suggest that the existing literature is indecisive (Beaudry & Schiffauerova, 2009; De Groot et al., 2009). In addition, researchers have realized that studies about agglomeration and spillovers should go beyond the dichotomy of specialization and diversity, and develop more accurate methods to define and describe the MAR and Jacobs externalities.

As a result, new approaches were proposed in later studies to address these problems. Porter (2003) points out that the distinction between localization economies and Jacobs' externalities is over simplified, as it focuses too much attention on an individual industry itself and overlooks how the industry is related to others. Porter proposes his concept of industry clusters, which refers to the geographic concentrations of linked industries. This approach places particular emphasis on the externalities between related industries. Following Porter's idea of clusters, recent studies show that industry clusters have significant impacts on regional development and the evolution of economic structure (see, for example, Delgado et al., 2010; 2014, among others). Frenken et al. (2007) more explicitly address this idea of relatedness and propose the concept of related variety. It is suggested that the inter-sector learning is more likely to happen between related industries, where cognitive distance is not too large nor too small (Boschma, 2005; Nooteboom, 2000). Thus the related variety, which measures the diversity of linked industries, is most relevant with the potential gains of Jacobs externalities. On the other hand, the unrelated variety, which measures the diversity of unrelated industries, is more associated with other regional features such as resilience. Many studies have found empirical evidence that the related variety has significant correlations with regional growth (Bishop & Gripaios, 2010; Boschma & Iammarino, 2009; Boschma et al., 2012; Hartog et al., 2012; Oort et al., 2014). And the related variety is also suggested to be closely associated with technology progress, innovation, and industry development strategy (Antonietti & Cainelli, 2011; Asheim et al., 2011; Castaldi et al., 2013; Neffke & Henning, 2013; Tavassoli & Carbonara, 2014; Zhang, 2011).

In more recent studies, researchers pay increasing attention to the roles of agglomeration economies and knowledge spillovers at more disaggregated industrial level, incorporating industrial heterogeneities in their approaches. For example, the Product Lifecycle Theory suggests that the actual impacts of different types of agglomeration externalities vary with the stage of the product lifecycle in an industry (Frenken et al., 2014; Potter & Watts, 2010). Specifically, while the importance of MAR externalities increases with the maturity of an industry, the significance of Jacobs' externalities declines when an industry matures (Duranton & Puga, 2004; Greunz, 2004; Henderson et al., 1995; Neffke et al., 2011) . It is also suggest that the opportunity to benefit from spillovers is likely to depend on the specific technologies, business patterns, and knowledge relevant to a particular sector (Beaudry & Schiffauerova, 2009; Henderson et al., 1995; Henderson et al., 2001). And in this paper we explicitly investigate how industry-specific features influence the roles of related variety on growth, seeking to reveal more details about how related variety, or Jacobs' externality, impacts sector growth under different circumstances.

3.3 Data and variables

We use employment growth as the proxy for a sector's economic performance. The sector employment data at the CZ level is derived from the US Census' County Business Pattern (CBP) dataset[22]. The annual dataset of CBP covers all counties' establishment and employment data at up to 6-digit NAICS non-agricultural sector level. However, due to confidentiality protection, not all counties' employment information is disclosed, especially at narrower sector levels. So

22 US Census: County Business Patterns. http://www.census.gov/econ/cbp/

we use the imputation method proposed by Autor et al. (2013) to estimate the missing data. Then each county's sectoral employment data are aggregated to the 691 CZs in the forty-eight US contiguous states[23] for each two-digit NAICS sector. The time frame for this research is 2000-2007, the period leading up to the recession. The calculation of the variables in our model requires consistent classification of industries, so data earlier than 2000s which are based on the SIC are not appropriate. A full description of the dependent variable, i.e., the employment growth rate of two-digit NAICS sectors at the CZ level during the period of 2000-2007, is shown in Table 3.1.

Table 3.1 Employment change of 2-digit NAICS sectors in CZs (2000-2007)

2-digit NAICS sector		Percentage change in employment of Commuting Zones[1]		
		Mean	Std. Dev.	Obs.[2]
11	Forestry, fishing, and related activities	-7.9	82.7	662
21	Mining	19.4	80.0	645
22	Utilities	-7.4	33.7	686
31	Manufacturing – food, textile, leather, etc.	-23.4	71.3	673
32	Manufacturing – wood, petroleum, chemicals, etc.	-13.1	48.4	678
33	Manufacturing – machinery, computer, electronics, etc.	-10.1	49.3	674
44-45	Retail trade	2.4	13.7	691
48-49	Transportation and warehousing	26.9	44.5	691
51	Information	80.5	52.1	684
52-53	Finance and insurance	8.6	21.6	691
54-56	Professional and business services	13.8	33.8	690
61-62	Educational services, health care, and social assistance	13.7	18.7	691
71-72	Arts, entertainment, recreation, etc.	12.6	17.5	691
81	Other services, except government	4.6	17.8	691

Notes:
[1] Calculated as 100×log(2007 employment/2000 employment).
[2] Observations with zero values in the initial year are omitted from our model.

23 We use USDA's Commuting Zone definition of 2000. See http://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas.aspx

Following Bishop & Gripaios (2010) and Frenken et al. (2007), we calculate the related variety of a two-digit NAICS sector in a region using the following entropy method:

$$Related\ variety_{r,i} = \sum_{j \in J_i} \frac{emp_{r,j}}{emp_{r,i}} ln\left(\frac{emp_{r,i}}{emp_{r,j}}\right) \tag{3.1}$$

where *emp* indicates the number of employed, and subscript *r* indicates the region (CZ) and *i* indicates the 2-digit NAICS sector. J_i is the set of all the industries at a more disaggregated level (5-digit NAICS sectors here) that fall exclusively under this 2-digit sector *i*, and these industries that belong to the same broader industry category are deemed "related" to each other. For a 2-digit industry *i*, if the employment is distributed more evenly among the sectors of its disaggregated level, then it has a greater value of related variety according to (3.1). In this research the calculation of regional variety is primarily built on the industry classification of NAICS, which is based on a production-oriented concept, meaning that it classifies industries according to similarity in the processes used to produce goods or services[24]. This NAICS method is commonly used in recent literature regarding to related variety, while some other methods are also used by researchers (see, for example, Boschma et al., 2012).

Here the related variety is calculated at 2-5 digit NAICS levels, meaning that as shown in

24 According to the US Census, http://www.census.gov/eos/www/naics/

equation (3.1), it is calculated for each 2-digit NAICS sector, using detailed employment data of 5-digit sectors under the 2-digit sector. In the next section our regressions are implemented across different sectors, so in order to make this variable of related variety comparable across different industries, we normalize it within each two-digit NAICS sector for the 691 CZs. Thus, regression coefficients in the following models should be interpreted as the marginal impact on a sector's employment growth from one standard deviation's difference in the related variety of *this sector*.

As to other variables, *unrelated variety* is the other form of regional variety proposed by Frenken et al. (2007), which measures the diversity of unrelated industries in a region. It is calculated as the entropy diversity between the 14 two-digit NAICS industries of each CZ, as in (3.2). $emp_{r,i}$ is employment of the i-th two-digit industry in the r-th CZ, while emp_r is the total employment of the r-th CZ. A higher value of this measure means a greater variety of unrelated sectors in region r.

$$Unrelated\ variety_r = \sum_{i=1:14} \frac{emp_{r,i}}{emp_r} \log(\frac{emp_r}{emp_{r,i}}) \tag{3.2}$$

Specialization of an industry in a CZ is defined as in (3.3). It is calculated as the proportion of region r's employment accounted for by sector i divided by the proportion of employment accounted for by this sector nationally. The impact of specialization on sector growth is mixed. On the one hand it is widely used as a measure of the MAR externality, which arises from the local concentration of the same economic activity. On the other hand, highly specialized industries may suffer from a convergence effect, leading to slowing development or even shrinking.

$$specialization_{r,i} = \frac{emp_{r,i}/emp_r}{emp_{US,i}/emp_{US}} \tag{3.3}$$

Urbanization is defined as a region's population density, which is from the US Census 2000. Urbanized regions may be more capable of providing some important institutions such as universities, large labs, trade associations, and other knowledge generating and transmitting organizations. In addition, populous areas also have larger local markets. So urbanization is usually viewed as a favorable factor for economic growth. But convergence effects may also arise in over-urbanized areas.

Average firm size has subtle impacts on growth. A smaller average firm size may be associated with more competition, which leads to better performance and more growth in the long run. On the other hand, larger firms can benefit from scale economies, or have greater market power and thus gain advantages. In our study average firm size is measured as average employment per establishment for each two-digit industry at the CZ level, and the establishment and employment data is also derived from the CBP. In order to make this variable comparable across different industries, we also normalize it within each 2-digit industry.

3.4 Related variety and local input-output linkages

Besides the above control variables that are commonly used in similar studies, there is another influential effect that is mostly overlooked by previous literature about related variety, i.e., the local input-output linkages. The intensity of local input-output linkages of an industry is strongly correlated with the related variety, as supply-demand connections are more likely to exist between sectors that are similar and related. When a sector is located close to a variety of related industries, there is a higher chance that it has many local input-output linkages and thus has more of its intermediate goods transacted locally. For example, Cainelli & Iacobucci (2012) find that firms located in a higher level of related variety have fewer incentives for vertical integration, as they have more channels through which to obtain intermediates from local suppliers. Andersson & Klaesson (2009) also suggest that there is an important connection between diversity and market accessibility in local economies. Therefore, the fact that related variety is associated with more growth can be the result of two possible mechanisms: first (Jacobs Externalities), the coexistence of diversified and related economic activities can promote knowledge spillovers; second (local input-output linkages), regions with higher related varieties have denser local input-output linkages and thus trade costs are lower. Either of these two effects can contribute to regional economic growth, but previous studies mostly built their arguments about the benefit of related variety on the first one, i.e., the Jacobs externalities. However, if it turns out that it is mostly the input-output effect rather than the former that explains the empirical correlation between related variety and regional growth, then the story of related variety will be much *less* interesting because it provides nothing new but is rather another proxy for the local input-output linkage or trade cost.

In fact it has been pointed out that there exist correlated but distinct mechanisms of agglomeration economies, and thus different indicators are needed to identify these varied effects precisely (De Lucio et al., 2002; Duranton & Puga, 2004), especially for the three Marshallian agglomeration economies: technological spillovers, input-output linkages, and labor pooling (Rigby & Essletzbichler, 2002). If we want to justify that related variety can lead to regional growth through the mechanism of knowledge spillovers, those correlated agglomeration effects such as labor pooling and input-output linkages must be appropriately controlled for. Compared with the input-output linkages, the impact of labor pooling is more likely to be accounted for by control variables such as the *specialization* which is described above[25]. Our prime concern here is to design a proxy variable for the local input-output linkages of each industry and include it as a control variable in our model.

A completely precise measure of the local supply-demand linkage requires full information of the local input-output table, which is not available at the CZ level. So we design a proxy variable to approximately reflect the intensity of local input-output linkages for each CZ-industry, which uses information from the national input-output table and CZs' employment structures. First, we apportion the total output value of each 5-digit sector to each CZ according to that CZ's employment share[26]. Second, for each industry in a CZ, we can estimate its intermediate demands based on the input-output coefficients from the national input-output table, with the assumption that local sectors' supply-demand relationships resemble those at the

25 The effect of labor pooling depends primarily on the total scale of a broad industry in which the narrower sectors share similar labor demands, rather than on how diverse these narrower sectors are. Thus the variable of specialization, which measures local employment quotient of the 2-digit industry, can also reflect the scale effect of labor pooling.

26 Because the US input-output table’s detailed sectors do not all exactly match the 5-digit NAICS sectors, we aggregate some 5-digit NAICS sectors to make them consistent with the US input-output table.

national level. Through these two steps we actually have estimated for each CZ all input-output linkages at the 5-digit NAICS level. Then the following measure is calculated for each 2-digit CZ-sector as the proxy for its intensity of local input-output linkages:

$$IO\ linkage_{r,i} = \frac{Value\ of\ bilateral\ intermediate\ demands\ that\ can\ be\ supplied\ locally_{r,i}}{Total\ value\ of\ all\ bilateral\ intermediate\ demands_{r,i}} \tag{3.4}$$

where the denominator is the sum of the values of bilateral intermediate demands between each pair of 5-digit sectors under this 2-digit industry[27], and the nominator is the value of these bilateral intermediate demands that can at most be supplied by local supplies, which considers not only the value but also the types of products that local sectors produce. In order to make this variable comparable across different sectors, just as was done with the related variety, we also normalize it within each industry. Figure 3.1 shows that, as we expect, this proxy variable of the local input-output linkage is strongly correlated with the related variety, which validates the need to include this measure as a control variable[28].

27 Here we only consider the 5-digit input-output linkages within this two-digit industry. Because the measure of related variety is the diversity of 5-digit sectors within a two-digit industry, thus what we need to control for is also exactly the bilateral intermediate demands that exist within this two-digit industry.
28 As we will see later, the multi-colinearity does not cause serious problems in each variable' significant level.

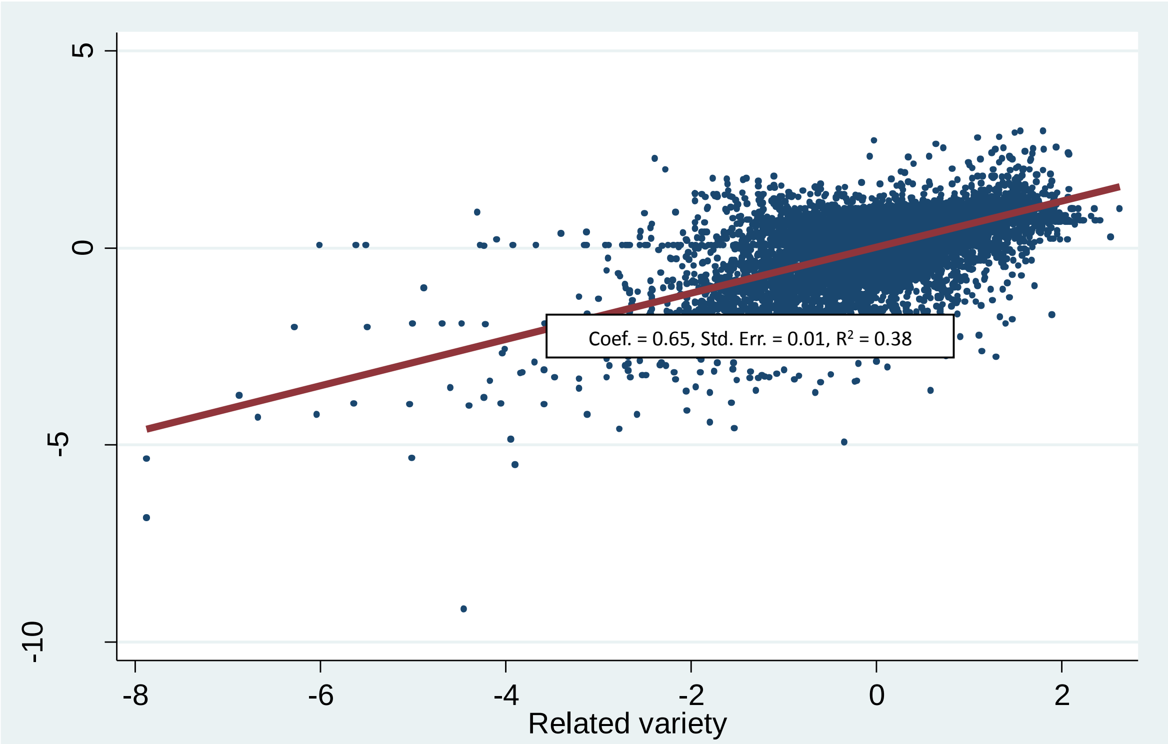

Figure 3.1 Figure 1. Related variety and local input-output linkages (2000)

N = 9568 CZ-industries

Among all the control variables, the related variety, specialization, average firm size, and local input-output linkages are CZ-industry specific, while the urbanization and the unrelated variety are CZ specific. Table 3.2 shows the covariance of these variables, as well as a cross-term of related variety and specialization that will be used later. All control variables are calculated as the initial year (2000) values. Beside the variables in Table 3.2, we also include two sets of dummy variables in our model. One is the industry fixed effects of the 14 two-digit sectors; and the other is for the nine US census division areas, which controls for the statistical errors of census-divisions and for other spatial fixed effects.

Table 3.2 Covariance of regional economic variables (2000)

	Related variety	Local input-output linkages	Unrelated variety	Specialization (log)	Urbanization (log)	Ave. firm size
Related variety	1					
Local input-output linkages	0.6198	1				
Unrelated variety	0.3196	0.3179	1			
Specialization (log)	0.1217	0.1691	0.1506	1		
Urbanization (log)	0.5324	0.492	0.4328	0.0008	1	
Ave. firm size	0.1068	0.2077	0.1977	0.3957	0.4004	1
Cross term: RV and SPE	-0.1116	-0.1316	-0.1201	-0.3493	-0.1265	-0.2351

N = 9537 CZ-industries.

3.5 Methods and results

First, we regress our basic OLS model for the impacts of related variety on industrial employment growth. Table 3.3 shows our main econometric specifications. The dependent variable is industrial employment growth rates in US Commuting Zones during 2000-2007. All the dependent variables are normalized so that the regression coefficients can be interpreted as elasticities. Standard errors are clustered by commuting zones in all models. Results from all columns of Table 3.3 suggest that, in general, related variety has significant and positive impacts on sector employment growth. And the negative coefficients of specialization suggest strong convergence effects of specialization, which outweigh the gains from MAR externalities. The proxy variable of local input-output linkage is added in Table 3.3(c), and its coefficient is significant and positive, which conforms to our expectation that local trade connections can reduce costs and promote growth. A more important finding is that, after controlling for this local input-output effect, the coefficient of related variety is still significant, but its magnitude drops nearly 20% compared with Table 3.3(b). That suggests the impacts of related variety, or the Jacobs externalities, would be over-estimated if the effects of the local input-output linkages were not appropriated controlled for.

Table 3.3 Related variety and CZ-industries' employment growth (OLS, 2000 ~ 2007)

	Dependent Variable: 100 ×log(2007 $emp_{r,i}$/2000 $emp_{r,i}$)		
	(a)	**(b)**	**(c)**
Related variety	3.45 *** (0.70)	3.75 *** (0.77)	3.07 *** (0.82)
Specialization (log)	-12.28 *** (0.91)	-10.78 *** (1.12)	-10.99 *** (1.13)
Unrelated variety		0.12 (0.76)	0.04 (0.77)
Urbanization (log)		-0.75 (1.33)	-1.19 (1.34)
Ave. firm size		-3.58 *** (1.27)	-3.58 *** (1.27)
Local input-output linkages			1.65 * (0.85)
Industry fixed effects	Yes	Yes	Yes
Census division fixed effects	Yes	Yes	Yes
Adj. R-Sq.	0.26	0.27	0.27

N = 9537 CZ-industries. Std. Err. are adjusted for 691 commuting zones.
**** p<0.01; ** p<0.05; * p<0.10.*

3.5.1 Manufacturing and non-manufacturing sectors

Results in table 3.3 highlight a positive connection between related variety and employment growth at the CZ-industry level. Next we investigate how this relationship varies across different types of industries. We start by distinguishing between manufacturing and non-manufacturing sectors. In table 3.4, columns (a) and (b) show estimation results of the basic model as in Table 3.3(c) for manufacturing and non-manufacturing sectors respectively. The results suggest that the impacts of related variety, as well as other independent variables, differ between these two types of industries. Compared with non-manufacturing sectors, manufacturing industries benefit more from related variety and local input-output linkages, but experience greater loss from the convergence effects of specialization and urbanization. And the coefficient of average firm size suggests that the effect of scale economies are prominent in manufacturing sectors, whereas for non-manufacturing sectors a smaller average firm size is more conducive for growth. In order to explicitly quantify the different impacts of related variety in these two types of sectors, in column 3.4(c) we introduce a set of interaction terms between all independent variables and a dummy variable (Manu Sector), which is equal to one for manufacturing sectors. The result indicates that compared with non-manufacturing sectors, for manufacturing sectors a one standard deviation difference in related variety leads to an additional 5.62 percentage points employment growth.

Next we look more closely at the three 2-digit NAICS sectors of the manufacturing industry (NAICS 31, 32, and 33), as in models (3.4-d), (3.4-e), and (3.4-f) respectively. The results suggest the impact of related variety is greater in technology-intensive sectors. Specifically, we find the largest coefficient in sector NAICS-33, which mostly consists of technology intensive sectors such as machinery, computer, electronic, etc. But for NAICS-31, which is comprised of relatively traditional industries, the coefficient of related variety is not significantly different from zero.

Table 3.4 Related variety and CZ-industries' employment growth (OLS, 2000 ~ 2007) -- manufacturing and non-manufacturing sectors

	Dependent Variable: 100×log(2007 $emp_{r,i}$/2000 $emp_{r,i}$)					
	Type of industry			**Manufacturing sectors**		
	(a) Manufacturing	**(b) Non-Manufacturing**	**(c) [1]**	**(d) NAICS-31**	**(e) NAICS - 32**	**(f) NAICS-33**
Related variety	8.69 *** (2.72)	2.22 *** (0.81)	2.39 *** (0.81)	4.53 (4.82)	9.52 ** (4.42)	14.99 *** (3.99)
Specialization (log)	-20.68 *** (2.56)	-8.90 *** (1.17)	-8.69 *** (1.17)	-19.76 *** (3.65)	-24.98 *** (5.77)	-16.31 *** (4.22)
Unrelated variety	2.82 (2.32)	-0.26 (0.78)	-0.32 (0.78)	-0.94 (4.60)	5.84 * (3.37)	0.14 (2.95)
Urbanization (log)	-6.83 ** (3.28)	0.81 (1.32)	0.78 (1.32)	1.52 (5.22)	-7.94 * (4.74)	-12.38 ** (5.08)
Ave. firm size	5.29 ** (2.17)	-5.26 *** (1.45)	-5.33 *** (1.45)	10.36 ** (4.17)	7.88 ** (3.17)	-3.54 (4.38)
Local input-output linkages	3.60 * (1.94)	1.40 (0.87)	1.56 * (0.86)	8.73 ** (3.96)	0.87 (2.52)	-2.55 (2.95)
Manu Sector × Related variety			5.62 ** (2.75)			
Industry fixed effects	Yes	Yes	Yes			
Census division fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N=	2025	7512	9537	673	678	674
Adj. R-Sq.	0.15	0.27	0.27	0.16	0.16	0.19

Note: In mode a-c, Std. Err. are adjusted for 691 commuting zones. Model d-f are estimated with robust error.
[1] Model (4-c) includes interaction terms of all the six independent variables of (4-b) and a dummy variable of manufacturing sector, but here we only reports the result of (Manufacturing ×Related variety).
**** p<0.01; ** p<0.05; * p<0.10.*

3.5.2 Agglomeration level

Agglomeration level is another factor that may influence the roles of related variety and knowledge spillovers in industry growth. For an industry a high level of agglomeration means most of its firms and employment concentrate in a few localities, whereas a low agglomeration level suggests they are scattered more evenly among different regions. We split the 14 two-digit NAICS industries by their national level of agglomeration measured by the Herfindahl index, and group them into high, median and low levels of agglomerations, where each level has 4 or 5 industries[29]. Regression results are shown in Table 3.5, and the Herfindahl index of each sector and agglomeration level are shown in Table 3.6. Models (3.5-a) through (3.5-c) in table 3.5 show the relationship between related variety and employment growth for industries of these three agglomeration levels respectively. Table 3.5 shows that the coefficients of related variety vary significantly among these three agglomeration levels, and have greater impact in the industries of median and high levels of agglomeration.

These results imply there may exist interaction effects between related variety and agglomeration levels. Some recent studies also indicate that specialization and regional variety may positively reinforce each other's impacts and contribute to a more consistent growth (Andersson & Klaesson, 2013; Fritsch & Slavtchev, 2010; Shuai, 2013). Specifically, increasing specialization in an industry will decrease local diversity, and this process in turn will hurt further growth as diversity can stimulate knowledge spillovers. Therefore, a higher initial level of diversity can alleviate the negative convergence effects of increasing

29 Empirical results are robust to adjusting marginal industries to different agglomeration groups.

specialization. Next we test this interaction effect more explicitly at the CZ-industry level by including a cross-term of related variety and specialization in the model, as in (3.5-d). The regression coefficient of this cross-term is significantly positive[30], which means there exist significant and positive interaction effects of related variety and specialization on sector employment growth. In other words, in those CZ-industries that have higher levels of specialization, related variety has greater contribution to employment growth. Of course, it can also be interpreted the other way, i.e., a higher level of related variety can reduce the convergence effect or growth penalty resulted from over-specialization.

30 For sensitivity analysis, first, we regress model 5-d for both manufacturing and non-manufacturing sectors. Second, we include the square terms of both the related variety and the specialization in model 5-d, in case the interaction effect just picks up the non-linear impacts of these two individual variables on the sector growth. Neither of these treatments essentially changes our results.

Table 3.5 Related variety and CZ-industries' employment growth (OLS, 2000 ~ 2007) -- agglomeration levels, and interaction effect of related variety and specialization

	Dependent Variable: 100 ×log(2007 $emp_{r,i}$/2000 $emp_{r,i}$)			
	Level of agglomeration			Interaction effects
	(a) Low	(b) Median	(c) High	(d)
Related variety	0.50 (1.02)	7.68 *** (1.81)	3.79 *** (1.39)	3.00 *** (0.81)
Specialization (log)	-11.05 *** (1.98)	-9.85 *** (1.65)	-26.52 *** (2.34)	-9.33 *** (1.05)
Unrelated variety	0.75 (1.15)	-2.97 ** (1.45)	2.24 *** (0.84)	0.16 (0.76)
Urbanization (log)	0.50 (2.97)	-6.50 *** (2.25)	4.28 *** (1.50)	-0.61 (1.33)
Ave. firm size	-3.63 (3.02)	-1.45 (1.46)	-3.48 ** (1.63)	-3.19 ** (1.26)
Local input-output linkages	-1.91 (1.21)	4.65 *** (1.54)	0.15 (1.55)	1.78 ** (0.87)
Specialization (log) × Related variety				4.51 *** (0.74)
Industry fixed effects	Yes	Yes	Yes	Yes
Census division fixed effects	Yes	Yes	Yes	Yes
N=	3407	3374	2756	9537
Adj. R-Sq.	0.11	0.15	0.47	0.28

Note: Std. Err. are adjusted for 691 commuting zones.
**** p<0.01; ** p<0.05; * p<0.10.*

Table 3.6 Herfindahl index of industries and levels of agglomeration

Level	NAICS	Herfindahl index	Sector description
Low	11	0.007008	Forestry, fishing, and related activities
	22	0.008742	Utilities
	32	0.00948	Manufacturing – wood, petroleum, chemicals, etc.
	44-45	0.009497	Retail trade
Median	71-72	0.01109	Arts, entertainment, recreation, etc.
	31	0.01173	Manufacturing – food, textile, leather, etc.
	81	0.01196	Other services, except government
	33	0.012	Manufacturing – machinery, computer, electronics, etc.
	61-62	0.01211	Educational services, health care, and social assistance
High	21	0.0129	Mining
	48-49	0.01628	Transportation and warehousing
	52-53	0.01818	Finance and insurance
	54-56	0.01853	Professional and business services
	51	0.02603	Information

3.5.3 Quantile regression

The above empirical work focuses on a sector's fixed traits, i.e., the type of industry and the level of agglomeration. Now we consider whether the effects of related variety vary between rapidly and slowly growing CZ-industries. We use quantile regression to estimate the basic model (3.3-c). Figure 3.2 provides graphical depiction of the quantile regression results, and it shows remarkable heterogeneity of the effects of related variety across the conditional growth distribution. Specifically, the impact of related variety is decreasing as the sector growth rate increases, and it even changes to be significantly negative for the highest 20% quantile.

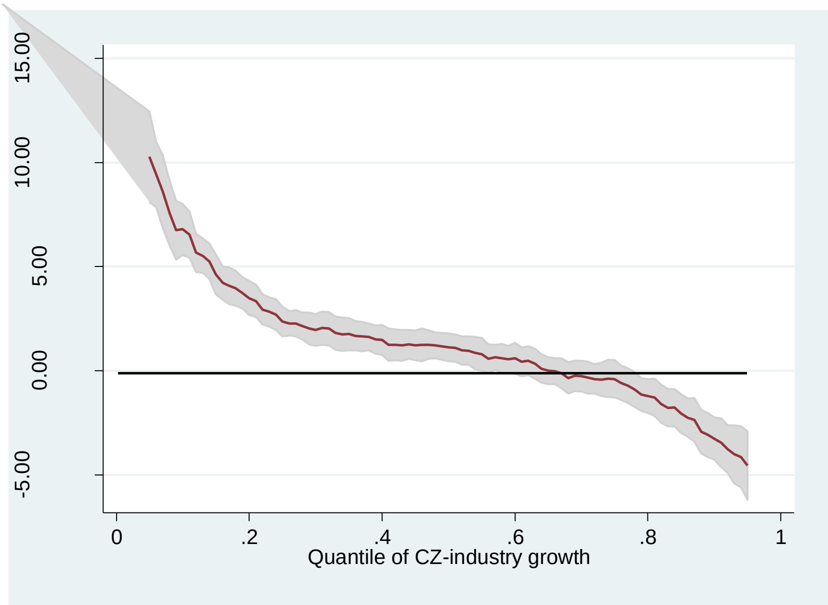

Figure 3.2 Quantile regression --
coefficient of related variety and CZ-industries' employment growth

Notes: Coefficient estimates and 95% confidence intervals.
Regression is based on the specification of mode 3-c.

As robustness checks, we re-estimate this quantile regression for manufacturing and non-manufacturing sectors as in section 3.5.1, and for the three agglomerations levels as in section 3.5.2, and all the results give us the consistent conclusion that slowly and moderately growing

CZ-industries are more likely to benefit from spillovers measured by related variety. This finding is similar to an earlier study of Fritsch & Slavtchev (2010), which suggests that industrial variety is associated with efficiency increase only for regions with low to median efficiency growth levels.

3.5.4 Sensitivity analysis

Finally, we test other alternative model specifications to check the robustness of our empirical results. First, CZ-industries with very small number of employed are vulnerable to shocks, making their growth rates more likely to change dramatically and become outliers. So we exclude those CZ-industries with initial employment lower than some threshold, such as 5, 10, or 20. Second, we control region fixed effects at the commuting zone level instead of the census-division level[31]. These two treatments are respectively applied to all models in table 3.3, table 3.4, table 3.5, and the quantile regressions. Results (available on request) show that all of the above main empirical conclusions are essentially unchanged.

3.6 Conclusion

In this paper we use an empirical model of sector employment growth at the US CZ level during 2000-2007 to investigate how the impacts of related variety vary among different sectors. And we devise a proxy variable to explicitly control for the effects of local input-output linkages, which is closely correlated with the related variety. The empirical results suggest that

31 In the above models, the region fixed effect is controlled by census division zones, because we want to keep the CZ specific variables such as the unrelated variety and urbanization, the coefficients of which we are also interested in. When the CZ fixed effect is included, these CZ-specific variables are omitted from the regressions.

in general related variety is associated with employment growth at the CZ-industry level, but this impact is over-estimated if the effects of local input-output linkages are not appropriated controlled for. We also find that related variety plays differential roles in the employment growth of sectors with heterogeneous characteristics. First, the impact of related variety on growth is greater for manufacturing than non-manufacturing industries. And within manufacturing industries, technology intensive sectors are more likely to benefit from related variety. Second, the connection between related variety and employment growth is stronger in sectors of median and high levels of agglomeration. In addition, there exist significant and positive interaction effects between related variety and specialization on sector growth, which means that if a CZ-industry has higher specialization levels, then related variety will have greater impact on its employment growth, or, a higher initial level of regional variety can dampen the convergence effects of over-specialization. Third, the quantile regression result highlights strong variation in the impacts of related variety at different growth level. Related variety is more likely to be at work for CZ-industries with low to median growth levels. These results suggest that diversification strategy as a policy instrument for boosting knowledge spillovers should be more region-industry based, and policymakers should not simply promote the general idea of variety for a region. Indeed, the role of regional variety in facilitating inter-sector learning is a complex and heterogeneous process, and there may not exist a simple and general relationship between variety and growth across all regions and sectors. Rather, the effectiveness of related variety in contributing to spillovers and growth is conditional on region-industry specific features.

4 Concluding Remarks

4.1 Summary of Findings

The three essays of this dissertation focuses on regional and urban development of the U.S., with particular emphasis on the confluence of industrial structure, entrepreneurship, international trade, and local labor markets. The first article proposes a new perspective to analyze entrepreneurship's roles in regional development; the second article studies how a regional economy can convert the adverse impacts of trade shocks into stimulus for new industry entry; and the third article investigates the relationship between industrial variety and economic growth at the region-industry level. Main findings of these three essays are summarized as following, respectively:

- A higher level of entrepreneurship can help a local economy more effectively mitigate the adverse shocks of import penetration. Possible explanations are that entrepreneurial activities can contribute to some favorable attributes of the regional economy, including flexibility in output structure, a diversified economic portfolio, and higher knowledge spillovers from trade-induced R&D activities.
- Trade shock brings about negative influences on a local economy in the short run, but it also offers stimulus to reconfigure the economic structure and develop new growth opportunities. Regions with higher levels of industrial variety and/or entrepreneurship are more capable of attracting new industry entrants when faced with import penetration, and thus their economies are, from an evolutionary perspective, more resilient in the

long run.

- Industrial variety is associated with inter-sectoral knowledge spillovers and can promote economic growth, but its effect is heterogeneous in different types of sectors. Two types of sectors are more likely to benefit from local industrial (related) variety, i.e., manufacturing industries that are technologically intensive, and geographically-agglomerated industries.

The primary approaches of these three essays are basically empirical, but some of the findings also offer significant theoretical implications. First, many researchers have studied different ways of incorporating entrepreneurial activities into formal frameworks of regional development (e.g., Acs et al., 2008; Qian & Acs, 2011), with focuses on entrepreneurs' roles of taking advantage of knowledge spillovers from incumbent firms and seizing opportunities in market niches. The findings in my 1st essay suggest that it is also possible to consider these entrepreneurial behaviors in the process of regional economic adjustment, which can be interpreted as another type of development in general. Second, the probability model of new industry entry that I develop in the 2nd essay is based on trade-induced factor reallocation effect, which has been widely applied in firm-level studies about international trade (e.g., Tybout, 2003; Mion & Zhu, 2013). In this article I show that under the condition of imperfectly factor mobility, this factor reallocation effect also applies to regional economies and offers important theoretical basis for analyzing the evolvement of industrial structure.

4.2 Future Work

The first two essays use different methods to study how adaptability is influenced by local economic conditions such as entrepreneurship and industrial variety. The Main innovation is that an evolutionary perspective towards resilience is adopted. The idea of evolutionary economic geography is widely discussed in resent literature about resilience, but to the best of my knowledge, this research is the first to conceptualize this new perspective in a framework of economic adjustment and to empirically test it with regional data. This approach also provides some possible avenues for future studies.

First, analysis on long-term development is necessary for evaluating the effectiveness of regional adaptability. Both theoretical and empirical frameworks in this dissertation are basically short to median-run in nature, as the models are based on an assumption of imperfect factor mobility, and the data spans for no more than a decade. So if we want to generalize the methods or the conclusions to a longer time scale, not only an appropriate dataset need to be available, but also a new theoretical model must be specified. In addition, when most of the factors like labor and capital are mobile in the long run, the proper proxy for economic performance may also need to be reconsidered, because in this case resilience should be evaluated at higher geographical levels (Metropolitan Area, state, or even country).

Second, this research focuses on the roles of entrepreneurship and industrial varieties in promoting regional economic resilience. But when relevant policy concerns arise, we can also extend the models in the above essays to investigate the impacts of other economic or social conditions on regional resilience, especially those conditions that have similar attributes as entrepreneurship or industrial variety. For example, labor market flexibility can be influenced by education attainment, labor union, wage policies, and culture. Similarly, regional business environment for new entrants is shaped by local tax policies, financial availability, natural amenities, input availability, etc. So all these factors are possible to influence local economic resilience and can be incorporated into the models of this dissertation in future studies.

The third essay studies industrial variety at the region-industry level and some new findings that are not identifiable at the regional level are obtained. A natural follow-up work is to step down to a finer level and investigate the impacts of industrial variety or other agglomeration economies at the firm level. Unlike a whole region or an industry, a firm or an establishment is the principle economic agent that makes independent decisions. So studies about firms' behaviors and strategies can reveal the roles of local industrial structure on economic activities at a more micro level. The expected findings will not only contribute to theories about agglomeration economies, but also have strong policy implications for industrial diversification strategies of a region.

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