ABSTRACT

Title of Dissertation: THREE ESSAYS ON AGGLOMERATION AND FIRM DYNAMICS

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Agglomeration economy has long been proposed to account for an individual firm's favor for denser environments. Previous strides have linked firm creation and productivity growth to the magnitude of agglomeration. This dissertation addresses three aspects of agglomerative impact on firms' dynamic that have not been adequately emphasized in the literature. Specifically, the research provides an understanding of how agglomeration affects firms' decisions on R&D investment, closure and relocation.

In Chapter 2, I develop a simple Cournot type, two-stage competition model that reveals firms tend to reduce their R&D investment more in denser locations than in less dense ones with the presence of knowledge spillover. This implies that local agglomeration strengthens the negative relationship between knowledge spillover and R&D efforts. I then use firm-level data from China to test this theoretical prediction. The Tobit model yields estimated results that are consistent with the theoretical

prediction. That is, the R&D effort is negatively correlated with knowledge spillover and the magnitude of the negative relationship increases along with localization agglomeration.

The impact of geographic concentration on firm survival is studied in Chapter 3. Agglomeration economy encourages firm birth and growth, while agglomeration diseconomy accelerates firm death. The net impact of agglomeration on firm survival depends on the relative strength of agglomeration economy and diseconomy. Drawn upon an establishment-level data from Maryland, the essay finds empirical evidence supporting the claim that urbanization negatively affects survival, while specialization, diversity and employment centers reduce hazards for some industries. The finding indirectly evidences that the firm selection effect contributes to the productivity advantage of big cities.

Firms frequently make spatial adjustments to accommodate their change in operation over time. Agglomeration economy could be one essential influence on a firm's relocation decision-making. Chapter 4 delves into the relocations of service firms within the Baltimore Metropolitan Region. The nested logit model shows a higher probability for firms choosing a location with a high level of agglomeration. The estimates suggest diversity might be more important than specialization at the margin for intra-metropolitan relocation. Also identified is a more prominent localization effect than urbanization effect on firm intra-metropolitan relocation.

THREE ESSAYS ON AGGLOMERATION AND FIRM DYNAMICS

by

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Dedication

To my wife, Jiemin Wu.

Thank you.

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Chapter 1: Introduction

The degree of concentration of population and firms is astonishing. According to the World Bank, in 2015 more than 54% of the world's population lived in cities and the number is still growing. In developed counties, urban population takes an even higher share. For instance, urban areas in U.S. hold 80.7 % of American population as of the year 2010; and almost three quarters (72.5 %) of the population in the EU-28 countries live in cities, towns and suburbs in 2014.[1] The story is no less striking for developing countries like China. Within 40 years, the urbanization rate in China increased from around 18% in 1978 to 57% in 2016.

Not just population, firm production is also concentrated in cities and even more intensely. McKinsey&Company reports, in 2010, the 30 largest cities in U.S. accounted for 44% of the country's total population while 50% of total GDP. In Western Europe, China and India, the GDP share generated in the 30 largest cities were also larger than their population share. The comparisons are 33% population share to 40% GDP share, 16% population share to 37% GDP share, 11% population to 24% GDP share in Western Europe, China and India respectively (McKinsey Global Institute, 2012). This observed spatially heterogeneous distribution of population and firm activities is far beyond what can be explained by chance, natural resources or comparative advantage (Puga, 2010).

One important response made by economists and urban scholars to explain the striking concentration of economic activities is the spatial increasing return to

[1] U.S. data is drawn upon 2010 Census and EU data is based on a report from statistical office of the European Union.

scale, usually known as agglomeration economy. Conceptual rationales of agglomeration date back more than a century ago when Marshall (1890) first hypothesizes the presence of agglomeration externalities upon his witnessing of firm concentration in British industry towns. He offeres three possible sources of agglomeration economy. The first one is the sharing of intermediate suppliers who produce under an internal increasing return to scale. The second is the labor market pooling which promotes the matching between employer's needs and employee's skills. And the third one is localized spillover of knowledge. As Marshall's observation primarily focuses on firms in the same industry, economists later identify that the agglomeration externalities stem from the geographic concentration of firms in the same industry as Marshall externalities. Contrary to Marshall, Jacobs (1969) believes urban diversity facilitates cross-industry spillover of information, ideas and techniques which nourish the creation of new products and services. The Jacobs externalities thus present the type of agglomeration economies arising from the concentration of a variety of firms and workers.[2]

Marshall externalities are represented by either localization or specialization. The former measures the scale of the concentration of a specific industry (own industry) and the latter captures the extent to which a city's employment is specialized in that industry. It is expected that a positive impact of the absolute scale of own industry on firms' productivity growth exists if localization economy is present. However, if own industry only takes a small share of the local economy, there might be a big congestion effect from other industries. The use of specialization as a percentage measurement somehow solves the problem

[2] Other externalities sources, like consumption advantage, rent seeking have been discussed in Rosenthal and Strange (2004). Although they matter the growth of large cities, they are not the focus of this dissertation.

of localization's failing to catch the downside from the concentration of other industries (i.e., the above-mentioned congestion effect). In that sense, specialization measurement estimates a net impact from the concentration of own industry (Rosenthal and Strange, 2004). Jacobs externalities, on the other hand, is expressed by either urbanization or diversity, with the former addressing the size of a city or an economic cluster and the latter considering whether the city or cluster is diversified. Urbanization captures Jacobs externalities because a larger local industry environment tends to be diverse (Henderson, 2003).

Despite the apparent differences between Marshall externalities and Jacobs externalities, they both address the benefits ultimately from the saving of transport costs (Glaeser, 2010). Here, the transportation costs are interpreted more broadly than the cost of delivering goods and services. For firms, the transportation costs also involve the difficulties in the exchange of people and ideas (Glaeser, 2010). As agglomeration facilitates the flow of workers and knowledge, it reduces firms' transport cost and helps achieve a more efficient production or innovation. Therefore, firms in denser areas (with stronger agglomeration externalities) should present higher productivity and more inventions on average than those located in less dense ones. Empirical studies indeed reveal large cities have more productive and innovative firms (Henderson, 2003; Carlino and Kerr, 2015), and are the hot spots of new firm creation (Rosenthal and Strange, 2003; Ni0u et al., 2015).

While agglomeration effect on firm productivity, birth and innovation has been well documented in literature, there are many other aspects of a firm's behavior could be affected by agglomeration. This dissertation will address three of the remaining puzzles that have not been emphasized enough in previous studies.

Specifically, in three related essays, it explores how agglomeration affects firms' decision on R&D investment, closure and relocation.

Chapter 2 contributes to the literature by both theoretically and empirically evidencing the relationship between localization agglomeration and firms' R&D investment. Studies in the industrial organization field hypothesize firms could save R&D investment by acquiring R&D outputs from other firms through knowledge spillover (d'Aspremont and Jacquemin,1988; Kamien et al., 1992). However, they generally neglect the fact that transmission of knowledge is difficult due to its tacit nature. Even today, transport of information still largely relies on face-to-face contact (Glaeser, 2010). Agglomeration of firms and workers determines the intensity of face-to-face interaction and bounds the magnitude of knowledge spillover. This then suggests the reduction in R&D investment of a firm should be positively affected by the magnitude of local agglomeration.

To test this idea, Chapter 2 develops a simple Cournot type, two-stage competition model that reveals firms tend to reduce their R&D investment more in denser locations than in less dense ones with the presence of knowledge spillover. This implies that local agglomeration strengthens the negative relationship between knowledge spillover and R&D efforts. The empirical test of my theoretic predictions is performed by using high-tech firm-level data from China. A technology similarity index is conducted as a proxy for knowledge spillover rate and the level of employment in the same two-digit CSICS industry is used as a proxy for localization agglomeration. The Tobit model is applied and yields estimation results that are consistent with the theoretical predictions.

Chapter 2 provides new proof to the existence of knowledge spillover. Empirical verification on knowledge spillover has been a challenging task since knowledge flows leave no paper trail by which they can be measured and tracked (Krugman, 1991). Previous studies indirectly study knowledge spillover by examining the geographical pattern of innovative output (primarily patent) and making a causal inference of knowledge accumulation to wage premium (Carlino and Kerr, 2015). However, the first approach is challenged since not all innovative output and ideas involved in knowledge spillover are patentable, and even if they are patentable, firms might prefer other approaches to protect their returns, for instance through trade secrecy and lead time advantage (Cohen et al., 2000). This suggests we should be cautious interpreting the results of patent analysis as it can't fully present the degree and distribution of knowledge spillover. Concern for the second approach is that agglomeration brings additional advantages other than knowledge spillover, for instance, better labor matching, that contribute to wage growth. Chapter 2 makes its contribution by offering an alternative in identifying knowledge spillover through the examination of agglomeration impact on firms' R&D investment.

The presence of knowledge spillover is especially important for start-ups; they could save a lot in R&D investment by freeriding information, ideas and techniques from mature firms. New firms also benefit from sharing and matching in concentration (Duranton and Puga, 2004). The proximity to incumbent firms offers new firms a constant market for skill, increases their attractiveness to employees, provides them chances of 'comparing shopping', and allows the experiment for an ideal production process (Maskell, 2001; Duranton and Puga, 2001). Abundant studies document the favor for localization agglomeration, urbanization agglomeration and diversity of new entrants (Guimarães et al., 2000; Rosenthal and Strange, 2003; Holl, 2004; Bhat et al., 2014; Jofre-Monseny et al., 2014). Niu et al. (2015) in addition report a positive impact of employment centers on firm birth beyond the general measure of localization and urbanization.

However, agglomeration may not promise a better survival for new firms. Large and dense urban environments are associated with higher wages, land rents, and more importantly, fierce competition among firms across all industries. A firm selection effect has been proposed stating less-productive firms would be eliminated from denser markets (Melitz, 2003; Melitz and Ottaviano, 2008; Saito and Gopinath, 2009; Comes et al., 2012; Accetturo et al., 2013).

In Chapter 3, the impact of agglomeration on firm survival is explored. It hypothesizes different attributes and types of agglomeration may impact differently on firm survival given their unique sources of agglomeration externality. The study is carried out in the state of Maryland using a firm-level dataset. Specialization, diversity and urbanization are separately measured within a short distance to a firm's location; and employment centers are identified following Giulinao and Small (1991). The results show urbanization is the primary force eliminating weak firms, while specialization, diversity and urbanization benefit the survival of mature firms in some industries. The findings in Chapter 3 reveal both agglomeration economy and firm selection effect are at work. Agglomeration encourages entrepreneurship and sharpens it through competition, and that leads to a more efficient and creative economy.

Closure, at the end, is not the only choice firms have when facing internal or external challenges. A lot of firms also make spatial adjustments to alternative places that better accommodate their changing needs over time. Chapter 4 then investigates how agglomeration influences firms in choosing an alternative location. A firm's favor for a particular agglomeration source at birth may not be sustained in its relocation. As discussed by Duranton and Puga (2001) in their life cycle model, firms' preference for specialization and diversity follows a dynamic manner: they favor a diversified environment for experimenting new ideas and immature production process, but prefer a specialized place for mass production. It suggests firms would relocate from diversified locations to specialized locations. Most empirical studies on firm relocation are conducted at city or metropolitan area level and they find a consistently positive impact of specialization while mixed impact of diversity in attracting relocated firms (Weterings and Knoben, 2013; Kronenberg, 2013; Holl, 2014).

Less evidence is provided regarding agglomeration effect on firms' intra-metropolitan relocation, which taking the majority share of all relocations. It is uncertain whether diversity or specialization at smaller geographic areas matters for firms' intra-metropolitan relocations. Chapter 4 addresses the problem by digging into the service firm relocations within the Baltimore Metropolitan Region. Alternative destinations for relocation are defined at zip code area level. The nested logit model is performed and reveals strong and positive impacts of specialization, diversity, localization and urbanization. The estimates suggest diversity might be more important than specialization for service firms' intra-metropolitan relocation. Evidence also supports a more prominent localization effect than urbanization effect on intra-metropolitan relocation.

Chapter 2: Localization, Knowledge Spillover, and Firm R&D Investment: Evidence from Chinese Cities

2.1 Introduction

Countries and regions worldwide often offer considerable tax credits, subsidies, and rewards to promote R&D investment of individual firms (Wallsten, 2000; Czarnitzki et al., 2011; Guo et al., 2016), based on the understanding that investment in innovation and knowledge contributes to long-run economic growth (Romer, 1986;1990). While firms positively respond to those incentives, there are external factors that influence their R&D investment (Smith et al., 2002; Czarnitzki and Hottenrott, 2011). One of them is knowledge spillover that disincentives firms to invest in their R&D investment. This negative effect of spillover on R&D is based on the premise that external knowledge (from R&D investment made by other firms) is substitute for internal knowledge (d'Aspremont and Jacquemin, 1988; Kamien et al., 1992).

Although the transport of information has never been easier as today, face-to-face interaction remains to be the most important way for knowledge transmission, especially for industries characterized by highly novel and complex technologies (Aharonson et al., 2007; Glaeser, 2010). Knowledge is quickly disseminating among neighboring high-tech firms in Silicon Valley through spying, imitation, and rapid interfirm movement of highly skilled labor (Glaeser, et al., 1992). Localized knowledge spillover has been viewed as one of the primary causes for the spatial concentration of economic activities (Marshall, 1895). Spillover, geographic concentration of firms and firm's R&D investment thus should intertwine themselves. If the strength of knowledge spillover is bounded by the magnitude of local agglomeration, its impact on firm's R&D investment reduction should be positively associated with agglomeration. However, previous theoretical research does not provide a clear answer on how the relationship between knowledge spillover and R&D investment is affected by agglomeration.

Limited empirical studies that examine the relationship between agglomeration and R&D investment seems to support the notion that firms invest less in R&D when they locate in economic clusters or cities (implying a larger agglomeration, especially localization agglomeration). Two different effects, however, have been proposed to explain the finding. One is the cost-saving effect, which emphasizes agglomeration provides the opportunity for firms to save self-financing R&D activities by freeriding R&D input of other similar firms (Lamin and Ramos, 2015; Leppälä, 2016). The other is the expropriation-avoidance effect, which refers to firms intentionally reduce R&D investment in dense areas due to strong knowledge expropriation (Leahy and Neary, 2007; Lee, 2009). It is not clear which effect plays a larger role, which is an empirical research question.

This essay attempts to fill in literature gap by investigating the relationship between knowledge spillover and firms' R&D investment with respect to localization agglomeration and by gauging the magnitude of the negative effect of localization agglomeration on R&D investment. I first develop a simple Cournot type, two-stage competition model in which firms simultaneously determine their non-cooperative R&D investment in the first stage and product output in the second one. The theoretic model shows that firms tend to reduce their R&D effort with the presence of knowledge spillover and to reduce more with a higher level of localization agglomeration. I then conduct empirical analyses by using Chinese firm-level data. The estimated results, as expected, are consistent with theoretic predictions. By comparing agglomeration effect on R&D investment by firm category (size and sector), the empirical examination suggests that cost-saving effect rather than expropriation-avoidance effect explains the negative impact of knowledge spillover on firm's R&D investment and the impact of localization agglomeration on the relationship between knowledge spillover and firm's R&D investment.

The essay is organized as follows. Section 2 reviews literature on agglomeration, knowledge spillover and R&D investment. Section 3 presents the model. Section 4 discusses data and variables. Section 5 interprets the results. Section 6 concludes the essay with final remarks.

2.2 Literature Review

Economists have long hypothesized the spillover of knowledge. Marshall (1895) first discusses how the learning process of firms fosters the spatial concentration of industries. He argues that agglomeration of firms facilitates the transfer of knowledge, so that "if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and it thus becomes the source of further new ideas" (page 352). Yet, knowledge spillover is the least understood factor driving the spatial concentration of economic activities (Henderson, 2007; Puga, 2010). The primary reason for this is due to a lack of direct measurement that captures knowledge flows across firms. Krugman (1991) points out that "knowledge flows are invisible, they leave no essay trail by which they may be measured and tracked" (page 53). Given those problems, the empirical verification of knowledge spillover can only rely on indirect evidence. Previous research studies localized knowledge spillover primarily through the examination of the geographical pattern of patents and patent citations (Henderson, 2007; Carlino and Kerr, 2015). The idea is that an inventor would be more likely to learn from other inventors and cite their works if they are geographically close to him/her. Empirical evidence shows patent citations disproportionately come from local areas and patent intensity is higher in denser markets (Jaffe et al., 1993; Carlino et al., 2007; Murata et al., 2013).

The spatial distribution of patents, however, do not necessarily parallels the spatial distribution of R&D investment. Literature investigating the relationship between patent and R&D expenditure reveals that patent intensity of a firm or an area is higher if the firm or area invest more in R&D and if its neighboring firms and areas with similar technologies invest in R&D (Griliches, 1990; Deltas and Karkalakos, 2013). This suggests that a firm or an area may achieve a high level of innovation by accessing to a large public "pool" of knowledge even with limited self-financing R&D activities (Koo, 2005; Aharonson et al., 2007).

The effect of knowledge spillover on R&D effort has been examined in aspatial industrial organization literature. d'Aspremont and Jacquemin (1988) first introduce the Cournot oligopoly model for firms engaging in a two-stage game. Identical firms conduct R&D activities in the first stage and then they become Cournot competitors and choose final good outputs in the second stage. They assume that the effective R&D output of firms comes from both self-financing R&D investment and R&D spillovers from other firms and conclude that a high level of knowledge spillover may lead to large total effective R&D output while firm's self-financing R&D input may decline at the same time. Since knowledge spillover is localized, this then suggests that the negative role of knowledge spillover in firm's R&D investment reduction should be strengthened by agglomeration. If that's the case, I should observe a negative relationship between agglomeration and firm R&D investment.

The literature reveals the negative impact of knowledge spillover on R&D investment may result from either a cost-saving effect or an expropriation-avoidance effect, or both. The flows of knowledge are bi-directional: while a firm freerides other firms' R&D output, its own R&D effort could be observed and utilized by rival firms (Poyago-Theotoky 1999; Amir et al., 2003; Lee, 2009). The magnitude of those two effects may differ across firms and industrial sectors. The cost-saving effect is more relevant to less technologically competitive firms, i.e. new entrants in knowledge-intensive industries. Those firms that are lack of the resources and experience in R&D activities hence rely heavily on external knowledge (Feldman, 1994, 2003; Aharonson et al., 2007). The expropriation-avoidance effect, on the other hand, is more relevant to technologically advanced firms. Leaders of high-tech firms may experience a more intensive outward knowledge spillover than inward knowledge spillover (Lee, 2009; Jo and Lee, 2014). The presence of knowledge expropriation then causes technologically advanced firms to reduce their R&D investment if they could not restrict the flow of ideas to others (Glaeser, et al., 1992).

It is interesting to note that both the cost-saving effect and expropriation-avoidance effect have important implication in location preference/choice for firms. Technology leaders are found prefer isolated locations while less technologically competitive firms favor agglomeration of industry activities (Shaver and Flyer, 2000; Alcacer and Chung, 2007; Jo and Lee, 2014).

Leppälä (2016) studies the location and R&D choice of firms with the same level of technological competence. He extends the Cournot model developed by d'Aspremont and Jacquemin (1988) into a three-stage game in which firms choose the distance between each other in the first stage and choose R&D and product outputs in the second and third stage respectively. He assumes that the level of spillover depends on spatial proximity between firms and concludes that localized knowledge spillover creates a centripetal force when three or more firms are involved in location choice. This means that the incentive to freeride on rivals' R&D efforts is stronger than the incentive to minimize knowledge leaking. Locating within an agglomeration implies more spillover and less own R&D investment, and hence a higher profit.

Although most studies reveal a negative relationship between knowledge spillover and firm's R&D investment, several essays mention that knowledge spillover could also raise firm's R&D expenditure. Cohen and Levinthal (1990) argue that in order to absorb and utilize incoming spillover of rivals' R&D, a firm would need to promote its absorptive capability, which largely depends on its own R&D level. Especially, investment in R&D is found to raise a firm's capability in absorbing external incremental/process R&D (Leahy and Neary, 2007). Besides absorptive capability, investment in R&D may also increase firms' ability in protecting their knowledge through secrecy, complexity, or lead time advantage (Cassiman and Veugelers, 2005). This is more relevant to product R&D with the premise that there is a considerable technological gap between technology leaders and laggards. There are, however, lack of empirical support for the positive relationship between knowledge spillover and firm's R&D investment.

It is worth pointing out that agglomeration could influence firm R&D investment in absence of knowledge spillover. Agglomeration aggravates competition that gives firms an incentive to invest more in R&D to pursue a product differentiation (Hughes, 1986). Coad and Rao (2010) find that firms' R&D expenditure is proportionate to their sales. If competition in denser markets limit the revenue that a typical firm can make, this then may suggest on average lower R&D expenditures of firms in location characterized by larger agglomeration.

Plenty empirical evidence on the relationship between agglomeration and R&D investment support a negative role of agglomeration in the literature. Suarez-Villa and Walrod (1997) study R&D activities of a sample of electronic manufacturing plants in the Los Angeles basin and find that clustered plants have lower R&D intensity than plants located in the periphery. Bagella and Becchetti (2002) report low R&D intensity of Italian manufacturing firms located in an industrial district. Beal and Gimeno (2001) investigate R&D investment of a sample of prepackaged software companies and conclude that agglomeration reduces firm's R&D commitment. Using survey data from the World Bank, Lee (2009) finds that locating in clusters decreases R&D intensity but only for firms in developed countries and regions. Lamin and Ramos (2015) show that the negative relationship between agglomeration and R&D investment is also presented in an environment with weak intellectual property rights protection. Most of these studies attribute the negative impact of agglomeration on R&D investment reduction to firm's attempt to reduce knowledge leakage.

Yet, a conclusive consensus has not been reached regarding the impact of firm agglomeration on R&D effort. For instance, Antonietti and Cainelli (2011) find little evidence of localization agglomeration influences R&D input. Smith et al. (2002) focus on R&D investment of Danish firms and conclude that while firms in rural municipalities present higher probability in committing R&D investment, they do not vary in R&D intensity compared to their counterparts in urban municipalities.

Zhang et al. (2014) identify an overall positive relationship between localization and R&D intensity of electronic and telecommunication firms in China. But, when disaggregate firms based on the value chain of industries, only the concentration of downstream firms generates a positive impact on R&D intensity while the concentration of midstream and upstream firms in most cases presents negative impact. One concern about the study's conclusion is that it measures localization based on administrative boundaries of prefecture cities. In China, prefectural cities are defined according to administrative arrangements that a typical prefectural city contains a city proper in the center and several scattered townships surrounded by less developed rural areas. The knowledge transferred between city proper and townships might be quite limited if any. For instance, the biggest prefecture city Bayingolin in Inner Mongolia is 462,700 km2. It is not likely for knowledge generated in city proper to spill across a vast sparsely populated rural area to its remote townships in the periphery.

In the following sections, I first examine the potential impacts of localization agglomeration and knowledge spillover on R&D investment by considering the spatial aspect of the Cournot model, and then testify the predictions of the theoretical model and address the concerns of previous studies with new empirical evidence.

2.3 The Model

I present a simple Cournot type model. Consider an industry of n identical firms that produce a homogeneous product. I define q_i as the output of firm i, and the output of the industry is determined by $Q = \sum_{i=1}^{n} q_i$. Assuming a perfectly segmented market and in each market, firms face a linear demand curve: $P = a - Q$. The initial production cost of all firms is the same c and $a > c$ (a is a constant).

Firms engage in a two-stage Cournot competition. They simultaneously decide non-cooperative R&D effort in the first stage and product output in the second stage. Following d'Aspremont and Jacquemin (1988), I assume that R&D outputs spill over in the first stage of the game. R&D outputs can be more easily recognized, absorbed, and utilized by other kindred firms. The production of R&D outputs subject to decreasing return as in previous studies. To simplify calculation, I define firm i's own R&D outputs y_i is the square root of its R&D investment x_i.[3] Besides own R&D outputs, firm i also adopts external R&D outputs in its product production. The applied effective (total) R&D outputs X_i are defined as:

$$X_i = \sqrt{x_i} + \beta \sum \sqrt{x_k} \tag{1}$$

where $\sum \sqrt{x_k}$, $k \neq i$, is the total effective R&D outputs of other firms in the industry, $\beta \in (0,1)$ is R&D spillover rate. The second term ($\beta \sum \sqrt{x_k}$) in Eq.1 then captures the applied external effective R&D output of firm i. I assume knowledge spillover only happens among firms in the same city. The proximity between firms located in the same city allows high labor mobility and chances of site observation and facilitates face-to-face communication which is important for knowledge spillover.

Effective R&D outputs are considered as a cost reduction or a quality-enhancing invention that affects the final good output that firms choose to produce in the second stage of the Cournot competition. In the second stage, the profit function of firm i is given by $\pi_i = (a - Q - c + X_i)q_i - x_i = \big(a - Q - c +$

[3] The industrial organization literature specifies the R&D investment a firm make as $x_i = \frac{1}{2}\gamma {y_i}^2$. $\gamma > 0$ is an inverse measure of the efficiency of R&D activity. This essay takes $\gamma = 2$ to ease calculations.

$\sqrt{x_i} + \beta \sum \sqrt{x_k})q_i - x_i$. The Cournot equilibrium output of the industry is obtained as follow: $Q = \frac{n(a-c)+(1+\beta(n-1))\sum\sqrt{x_i}}{n+1}$. The equilibrium output of each firm is $q_i^* = \frac{Q}{n}$.

The profit function in stage two thus can be rewritten as $\pi_i = (q_i^*)^2 - x_i$. By applying the first order condition to the profit function and assuming that firms make a symmetric R&D choice, that is $x_i = x$ and $y_i = y$, $\forall i \in n$, I obtain a firm's own optimal R&D output as:[4]

$$y^* = \frac{(a-c)(\beta+(1-\beta)n)}{(n+1)^2-(\beta+(1-\beta)n)(1+\beta(n-1))} \tag{2}$$

Eq.2 shows that firm's R&D output from self-financing investment is jointly determined by initial market size ($\sigma = a - c$), number of firms in industry (n), and knowledge spillover rate between firms (β).

From the partial derivatives of Eq.2 and $\frac{\partial x^*}{\partial y^*} > 0$,[5] I obtain the following relations: $\frac{\partial x^*}{\partial \sigma} > 0$, $\frac{\partial x^*}{\partial n} < 0$ and $\frac{\partial x^*}{\partial \beta} < 0$. Those relations reveal that a larger market size would imply a larger R&D investment ($\frac{\partial x^*}{\partial \sigma} > 0$), localization agglomeration is negatively related to R&D investment ($\frac{\partial x^*}{\partial n} < 0$), and a higher spillover rate causes a lower R&D investment ($\frac{\partial x^*}{\partial \beta} < 0$).

[4] The first order condition is: $x_i = \frac{\left(a-c+(2\beta-1)\sum\sqrt{x_k}\right)^2(\beta+(1-\beta)n)^2}{((n+1)^2-(\beta+(1-\beta)n)^2)^2}$, so that I have $y_i = \frac{(a-c+(2\beta-1)\sum y_k)(\beta+(1-\beta)n)}{(n+1)^2-(\beta+(1-\beta)n)^2}$.

[5] $\frac{\partial y^*}{\partial \sigma} = \frac{(\beta+(1-\beta)n)}{(n+1)^2-(\beta+(1-\beta)n)(1+\beta(n-1))}$, $\frac{\partial y^*}{\partial n} = -\frac{\sigma\left((n-1)(1-\beta+\beta^2)\left((1-\beta)n+(1+\beta)\right)+3\beta\right)}{((n+1)^2-(\beta+(1-\beta)n)(1+\beta(n-1)))^2}$, and $\frac{\partial y^*}{\partial \beta} = -\frac{\sigma(n-1)((n-1)\beta+1)\left((2-\beta)n+\beta+1\right)}{((n+1)^2-(\beta+(1-\beta)n)(1+\beta(n-1)))^2}$. Thus, I have $\frac{\partial y^*}{\partial \sigma} > 0$, $\frac{\partial y^*}{\partial n} < 0$ and $\frac{\partial y^*}{\partial \beta} < 0$ (since $0 \le \beta \le 1$, $n > 1$, and $a > c$).

The model also concludes an interesting finding. That is: even if knowledge spillover is absent ($\beta = 0$), there may still exist a negative relationship between local agglomeration and R&D investment (as illustrated by $\frac{\partial x^*}{\partial n} < 0$). The specification of the production function indicates that R&D investment is upper bounded by the final good output q^*, which declines along with the number of firms ($\frac{\partial q^*}{\partial n} < 0$) when $\beta = 0$.[6]

A way to identify the spillover effect on R&D investment is to examine the sign of the cross partial derivative of x^* over n and β($\frac{\partial^2 x^*}{\partial n \partial \beta}$). I show that $\frac{\partial^2 x^*}{\partial n \partial \beta} < 0$.[7] This means that the negative effect of knowledge spillover on R&D investment increases with localization agglomeration.[8]

When spillover rate is exogenous, as assumed in my model, an increase in the number of agglomerated firms should not change the knowledge that a firm

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[6] Agglomeration studies reveal that there are diseconomies associated with concentration, including high land rents and wages, traffic congestion and density-related pollution (Richardson, 1995; Folta et al. 2006). The agglomeration diseconomies may discourage firm R&D activities and lead to a negative impact of localization on R&D investment.

[7] $$\frac{\partial^2 y^*}{\partial n \partial \beta} = \frac{\sigma\big((-\beta^2+\beta-1)n^2+(\beta^2-\beta+1)\big)\big((3\beta^2-6\beta)n^2+(-6\beta^2+8\beta-4)n+(3\beta^2-2\beta+1)\big)}{((n+1)^2-(n-\beta(n-1))(1+\beta(n-1))^3}$$

$$+\frac{\sigma\big((2\beta^2-2\beta+2)n+(-2\beta^2+2\beta+1)\big)\big((\beta^2-2\beta)n^3-(3\beta^2-2\beta+1)n^2+(2\beta^2-2)\big)}{((n+1)^2-(n-\beta(n-1))(1+\beta(n-1))^3}.$$ By taking extreme values of β, it can be derived that the denominator of the cross partial derivative is larger than $2n+1$, so is larger than 0, and the nominator is smaller than $\sigma(-10/3n)$, which is smaller than zero. So $\frac{\partial^2 y^*}{\partial n \partial \beta} < 0$.

[8] It should be noted that although localization agglomeration and knowledge spillover reduce self-financing R&D investment, they do not necessarily lead to lower effective R&D outputs that firms utilize in their product production. Let E^* denotes the equilibrium external effective R&D outputs firms apply through spillover. $\frac{\partial E^*}{\partial n} = \frac{\sigma\beta\big((\sqrt{3}+2-\beta)+(\sqrt{3}+1+\beta)n\big)\big((\sqrt{3}-1-\beta)n+(\sqrt{3}-2+\beta)\big)}{((n+1)^2-(n-\beta(n-1))(1+\beta(n-1))^2}$ and $\frac{\partial E^*}{\partial \beta} = \frac{\sigma(n-1)\big((n+1)^2(n-2(n-1)\beta)-(n-\beta(n-1))^2\big)}{((n+1)^2-(n-\beta(n-1))(1+\beta(n-1))^2}$. From Eq.2, I obtain $\frac{\partial E^*}{\partial n} > 0$ when $\beta > 0$, implying the absorbed external effective R&D outputs rises with localization agglomeration when knowledge spillover is present. Also, I have $\frac{\partial E^*}{\partial \beta} > 0$, suggesting firms can acquire more external effective R&D outputs when spillover rate is higher.

could learn from other firms. However, larger and denser agglomeration may augment the match of knowledge and information, and raise the efficiency of knowledge exchange through more frequent formal and casual contacts between firms and employees (Glaeser et al., 1992; Glaeser, 2010). This suggests spillover rate could be endogenous, which is partially determined by the magnitude of agglomeration. In other words, an increase in the number of agglomerated firms would allow a firm to learn more knowledge from another firm.

Assume spillover rate $\beta(n,\gamma)$ as a function of number of firms n in an industry and technological similarity γ between kindred firms. By assumption, $\frac{\partial\beta}{\partial n} > 0$ and $\frac{\partial\beta}{\partial\gamma} > 0$. Define x^E and y^E as the equilibrium R&D investment and own R&D outputs given endogenous spillover rate, I have $\frac{\partial x^E}{\partial n} = (\frac{\partial y^*}{\partial \beta}\frac{\partial \beta}{\partial n} + \frac{\partial y^*}{\partial n})\frac{\partial x^E}{\partial y^E} < 0$, $\frac{\partial x^E}{\partial \gamma} = \frac{\partial y^*}{\partial \beta}\frac{\partial \beta}{\partial \gamma}\frac{\partial x^E}{\partial y^E} < 0$.[9] This means that 1) the spillover rate, which may or may not be affected by the magnitude of localization agglomeration, does not change the negative relationship between localization and R&D investment; and 2) technological similarity between firms is expected to reduce R&D investment as long as knowledge spillover is present. I also have $\frac{\partial^2 x^E}{\partial n\,\partial\gamma} = (\frac{\partial y^*}{\partial \beta}\frac{\partial^2 \beta}{\partial n\,\partial \gamma} + \frac{\partial^2 y^*}{\partial n\,\partial \beta}\frac{\partial \beta}{\partial \gamma})\frac{\partial x^E}{\partial y^E}$, so the negative indirect impact of localization and technological similarity on R&D investment sustains if $\frac{\partial^2\beta}{\partial n\partial\gamma} \geq 0$. The negative relationship is violated only when $\frac{\partial^2\beta}{\partial n\partial\gamma} \leq -(\frac{\partial^2 y^*}{\partial n\,\partial \beta}\frac{\partial \beta}{\partial \gamma})/(\frac{\partial y^*}{\partial \beta}) < 0$. The violation, however, may never happen. Intuitively, it is quite unlikely to see the relationship between technological similarity and spillover rate is negatively affected by localization. If spillover rate

[9] By using the equations in the footnote 5.

is simply determined by technological similarity, then $\frac{\partial x^E}{\partial n} = \frac{\partial x^*}{\partial n}$, $\frac{\partial x^E}{\partial \gamma} = \frac{\partial x^*}{\partial \beta}$ and $\frac{\partial^2 x^E}{\partial n \partial \gamma} = \frac{\partial^2 x^*}{\partial n \partial \beta}$. Thus, I conclude that my model predictions on the relationships among knowledge spillover, R&D investment, and localization agglomeration hold constant even knowledge spillover (rate) is endogenous with localization agglomeration.

To investigate the effect of knowledge spillover on firm's R&D investment and the impact of localization on the effect, I use the following reduced form in my empirical examination. The baseline model is expressed as:

$$x_{ijk} = \beta_0 + \beta_1 N_{jk} + \beta_2 T_{ijk} + \beta_3 M_k + \beta_4 C_{ijk} + \varepsilon_{ijk} \tag{3}$$

where N_{jk} is the number of firms in specified industry j in city k, T_{ijk} is the technological similarity between firm i and other firms in industry j in city k, M_k is the market size of city k, and C_{ijk} is a vector of control variables capturing other firm, industry and city specific characteristics. It is expected that $\beta_1 < 0$, $\beta_2 < 0$, and $\beta_3 > 0$ according to my model.

Eq. 3 is expanded by adding an interactive term to examine the impact of localization on spillover effect on R&D investment. It is expressed as:

$$x_{ijk} = \beta_0 + \beta_1 N_{jk} + \beta_2 T_{ijk} + \beta_3 M_k + \beta_4 C_{ijk} + \beta_5 N_{jk} \times T_{ijk} + \varepsilon_{ijk} \tag{4}$$

β_5 is expected to be negative.

2.4 Study Area, Data and Variables

An implicit understanding of agglomeration economies is that their micro-foundations (such as input sharing, labor pooling, labor matching, and knowledge spillover) have a geographic limitation. This makes China an interesting case to examine because China has both physical and institutional barriers that disintegrate its domestic markets.[10] From a physical aspect, China is heavily dependent on land-based transport networks (roads, railroads, and water transport) for inter-regional movement of people and goods. In 2006, volumes of movement of people and goods by roads and railroads accounted for 98% and 86% respectively.[11] China has been investing in highways and high-speed railroads at amazing rates in the past two decades. But the coverages of the road and railroad networks in 2007 were still pretty low, compared to developed countries. For instance, in 2007, the highway density (length/area) was 0.81 km per 100 sq. km in China, much lower than 2.07 km per 100 sq. km in the USA and 4.82 km per 100 sq. km in the European Union. The railroad density was 0.56 km per 100 sq. km in China, while the USA and the European Union were 0.97 and 1.47 km per 100 sq. km, respectively.[12]

Institutional barrier refers to regional protectionism that is blamed for the fact that China is more integrated into the world's economy but less to its own domestic markets (Young, 2000; Poncet, 2003). Anecdotal examples include Henan and Anhui provinces banning tobacco products from Guizhou province, and Shenzhen city banning sales of a newspaper from Guangzhou city (Gilley, 2001). A bottle of Beijing's Yanjing's Beer was sold at the equivalent of $0.18 in Beijing but $1.00 in Sichuan province (Gilley, 2001). The domestic market segmentation in China is indirectly reflected on the shipping distance of goods. It was only 69 kilometers by highway and 757 kilometers by railway in 2007, much lower than those in Europe and USA.[13] Despite the tremendous development in transportation

[10] China's market fragmentation fits my model well too.
[11] Data is drawn from China Statistical Yearbook 2007.
[12] Data is drawn from European Road Statistics 2010.
[13] In USA, a ton of rail shipments traveled on average 662 miles (1059 kilometers), and a ton of truck shipments traveled 158 miles (253 kilometers) in 2002

network, the average shipping distance of goods increased by margin. For example, in 1990-2007, the average shipping distance of goods by railway increased by only 7.4%, much less than the growth rate of 94.8% in the average travel distance of railway passengers and of 34.7% in the total length of operating railways.

The primary data source of the essay is the Annual Survey of Industrial Firms (ASIF) conducted by National Bureau of Statistics (NBS) of China. It provides detailed information on firms' location, industry, ownership structure, employment, and financial status of all state-owned enterprises (SOEs) and non-state-owned manufacturing enterprises with annual sales of 5 million RMB or more (above-scale enterprises). The above scale enterprises account for 90% of total output and revenue of all industrial firms, making the dataset a good representative of the national economy. Data from 2007 is drawn to generate dependent variable, and data from 2006 is used to measure the scale of localization and generate part of the control variables.[14] The rest control variables are constructed by using data from China's City Statistics Yearbook, which provides economic and demographic data for cities.

Firms are classified according to Chinese Standard Industry Classification System (CSICS 2002). I examine only high-tech industries because they more likely engage in innovative activities than conventional machinery industries, and are the primarily targeted industries under China's national strategy of building an

(http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/freight_shipments_in_america/html/entire.html).

In European Union, the 2014 data suggest 56% of road shipment volumes are longer than 300 kilometers, and only 7.5% of volumes are within 50 kilometers (http://ec.europa.eu/eurostat/statistics-explained/index.php/Road_freight_transport_statistics#Longer_distance_class_recorded_highest_rise_compared_with_2010).z

[14] China has published fewer data items for the industrial surveys after 2008 than before. Key variables such as R&D input, are no longer available now. The year of 2007 is the latest with the most data publicly available.

innovation-oriented country. The high-tech industries are defined in High-Tech Industries Classification 2013 by the NBS.[15] High-tech firms located in city-proper areas (*Shiqu*) of prefecture-level cities are included in the sample.[16] In 2007, there were 14,828 high-tech firms in 273 cities. Industries are excluded if they are vaguely defined or defined as a combination of different industries, i.e. CSICS 4090 Other Electronic Equipment. I end up with 12,933 firms in the sample.

I use both absolute and relative measures for firm's R&D investment. Total R&D spending (*RD*) captures the size of firm's R&D investment. I use R&D intensity as the relative measure (*RDI*). R&D intensity is the ratio of R&D spending over revenue of firms. These two indicators are most frequently used to monitor the resources firms devote to science and technology research and development (OECS, 2012).

In my data sample, about 66% of firms did not make any R&D investment. With so many zero entries, the OLS estimator might be biased. Tobit model can provide a consistent estimation. I hence apply Tobit model to deal with a large number of zeros in the dependent variables. Both *RD* and *RDI* are censored at 0. I assume log normal distribution of uncensored R&D investment. Figure 2.1 presents the distribution of uncensored R&D data.

[15] The document provides detailed descriptions of the direct relationships between classification systems, so industries defined by CSICS 2013 can be matched by those defined by CSICS 2002.
[16] About 33% of high-tech firms that located in non-city-proper areas (suburban and rural areas) are excluded for analysis. Refer Ding (2013) for a better discussion of the definition of city-proper and non-city-proper. In this essay, city always represents city-proper areas (*Shiqu*).

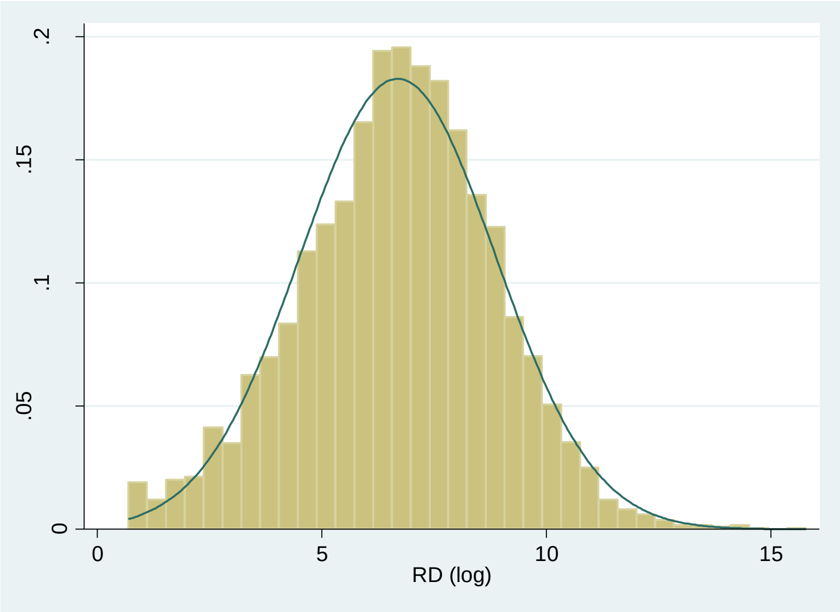

Figure 2.1 Density Distribution of Uncensored R&D investment

Previous studies measure technological similarity using patent data (Deltas and Karkalakos, 2013; Younge and Kuhn, 2016). However, as discussed by Cohen et al. (2000), patent application bias firms' real technology portfolio. A firm may apply technologies that are not patentable or have already been patented by other firms. The incentive for patent application is also heterogeneous among firms. For instance, given the cost of patent litigation, smaller firms are less likely to pursue patents (Cohen et al., 2000). In contrast, big firms often apply for similar patents on close substitutes for their primary patent to block follow-on patenting by rival inventors (Carlino and Kerr, 2015).

Spillover rate is primarily determined by the technological similarity and absorptive capability of firms (Cohen and Levinthal, 1990; Wiethaus, 2005; Leahy and Neary, 2007). But absorptive capability is not observable. Empirical studies thus use technological similarity between firms to measure the possibility of knowledge spillover. The technological distance between firms underlies whether and to what degree external knowledge is transferable or absorbable (Jaffe, 1986).

It is easy for a firm to recognize potential applications of and effectively absorb external knowledge from other firms if they share a similar production technology.

I then develop a technological similarity index (*TS*) as a proxy for knowledge spillover rate among firms using industrial classification codes. The technological similarity index is constructed as

$$TS = \frac{same\ 4d\ emp \times 3 + same\ 3d\ different\ 4d\ emp \times 2 + same\ 2d\ different\ 3d\ emp}{same\ 2d\ emp \times 3}$$

where $same\ 2d\ emp$ is the employment of the same 2-digit CSICS industry in the same city, $same\ 4d\ emp$ is the employment of the same 4-digit CSICS industry in the same city, $same\ 3d\ different\ 4d\ emp$ is the employment of the same 3-digit CSICS industry subtracts the employment of the same 4-digit CSICS industry in the same city, and $same\ 2d\ different\ 3d\ emp$ is the employment of the same 2-digit CSICS industry subtracts the employment of the same 3-digit CSICS industry in the same city. If a firm co-locates with other firms in the same 2-digit CSICS industry, then the technological similarity index will fall between 0.33 and 1. If a firm is the only firm in its 2-digit CSICS industry in the city, *TS* is set to be zero.

I use employment of firms in the same 2-digit CSICS industry in the same city (*LOC*) as the proxy of localization agglomeration.[17] I use employment rather than establishment number to measure agglomeration for two reasons. First, firms are not identical, employment can better capture the actual magnitude of agglomeration. Second, the transfer of knowledge largely relies on the interaction between people.

[17] CSICS 2-digit classification is equivalent to NAICS 3-digit classification.

A set of firm-specific control variables is included in the estimation. *SIZE* measures a firm's employment. *AGE* is the number of years a firm has survived since its birth. The impact of ownership is captured by two dummies *STATE* and *NONCON*. *STATE* equals 1 if the state owns the firm or is the controlling shareholder, while *NONCON* equals 1 if the firm is owned or controlled by foreign investors or by investors from Taiwan, Hong Kong, and Macau. If both *STATE* and *NONCON* equal 0, the firm is a private mainland firm. *EXPORT* calculates the portion of output that has been exported. *INDRD*, which is calculated by summing up R&D investment of all co-located same 2-digit CSICS firms in 2006, controls the heterogeneous city specific industry R&D level. *COMP* is a competition indicator, calculated as the number of firms per workers in an industry in a city relative to the number of firms per worker in that industry in the country (Glaeser et al., 1992). By its definition, the indicator can also be interpreted as the relative average firm size of an industry in a specific city. The coefficient of *COMP* thus will have a dual implication since average firm size is also a typical indicator of entrepreneurship. In addition, three variables are used to control city specific features. *POP* is the population of a city and is expected to capture the effects associated with market size and urbanization agglomeration. An industrial Herfindahl–Hirshman index (HHI) is created by summing the square of industry employment share at 3-digit CSICS level. *DIVERSITY* measured by 1 subtracting HHI reflects how Jacob's externality affects R&D expenditure. *HUMAN* is the number of college students in a city, representing the human capital level of the city. Finally, industry fixed effect is considered in the final models to gauge the heterogeneous nature of industry R&D preference. All continuous variables are included in their log forms.

Table 2.1 Descriptive Statistics of Variables

Variable	Description	Mean	Std. Dev.	Min	Max
RD	Firm R&D spending (RMB, in log form)	2.263	3.411	0	15.782
RDI	Firm R&D spending/revenue	0.012	0.048	0	2.349
TS	Technological similarity in the same indsutry in city	0.491	0.152	0	1
LOC	Employment number in the same indsutry in city (in log form)	10.351	2.296	0	13.757
SIZE	Firm employment number (in log form)	5.061	1.310	0.693	12.145
AGE	Firm age (in log form)	2.064	0.744	0	6.011
STATE	Dummy; 1 if state owned	0.112	0.315	0	1
NONCON	Dummy; 1 if non-continental owned	0.381	0.486	0	1
EXPORT	Percentage of exported output	0.253	0.392	0	5.839
POP	Population in city (million, in log form)	6.090	1.002	2.708	7.504
DIVERSITY	Industy diversity in city	0.947	0.061	0.186	0.981
HUMAN	College students in city (thousand, in log form)	11.540	1.475	0	13.380
INDRD	Total R&D spending in the same indsutry in city (RMB, in log form)	11.301	3.386	0	16.114
COMP	Competition index for firms in the same indsutry	1.390	1.023	0	21.422

Table 2.1 presents the descriptive statistics of the variables. The high-tech firms on average have 466 workers and invest about 3.5 million RMB, which about 1.2% of their revenue in R&D. The average co-located workers in the same 2-digit industry are around 17 thousand and the average technological similarity between high-tech firms and their neighboring firms in the same 2-digit industry is 0.491. About 11% of firms are owned or controlled by the state, and 38% of firms are owned or controlled by foreign investors or by investors from Taiwan, Hong Kong

and Macau. On average, the high-tech firms export a quarter of their products abroad.

2.5 Results

2.5.1 Basic estimation

Table 2.2 presents the basic estimates of Tobit model. As expected, my estimated results reveal that knowledge spillover disincentives firm's R&D investment and the negative impact of knowledge spillover on firm's R&D investment is not trivial. The coefficient of the technological similarity index is significantly negative. The estimated values of the coefficient show that a 1% increase of technological similarity would result in 0.2% reduction in R&D spending and 0.19% decrease in R&D intensity without controlling industry fixed effect, or 0.4% reduction in R&D spending and 0.29% decrease in R&D intensity when industry fixed effect is considered.[18]

As expected, the results show that the variable of localization agglomeration has a negative sign significant at 99% level. The estimated values of the coefficient suggest that a 1% increase in the employment of same 2-digit firms leads to 0.47% decrease in a firm's R&D spending without controlling industry fixed effect (Column 1) or 0.3% decrease when industry fixed effect is controlled (Column 2). Both values of the variable's elasticity conclude that the negative impact of localization agglomeration on R&D is substantial. I obtain a similar conclusion by using R&D intensity measure. The elasticity of R&D intensity is calculated by using the coefficients in Column (4) and Column (5). They illustrate a 1% increase in the

[18] These elasticities are calculated at the mean of the variables.

employment of same 2-digit firms reduces a firm's R&D intensity by 0.32% or 0.23% depending on the control of industry fixed effect.

Table 2.2 Agglomeration and Firm R&D Expenditure

	Dependent variable: RD			Dependent variable: RDI		
	(1)	(2)	(3)	(4)	(5)	(6)
TS	-1.136**	-2.295***	-2.641***	-1.809E-02***	-2.728E-02***	-3.380E-02***
	(0.536)	(0.553)	(0.386)	(6.990E-03)	(7.249E-03)	(5.475E-03)
LOC	-1.323***	-0.849***	-0.617***	-1.496E-02***	-1.084E-02***	-8.334E-03***
	(0.088)	(0.099)	(0.061)	(1.155E-03)	(1.299E-03)	(8.573E-04)
LOC×TS			-0.757***			-9.663E-03***
			(0.127)			(1.799E-03)
SIZE	2.062***	2.157***	2.161***	1.388E-02***	1.491E-02***	1.496E-02***
	(0.071)	(0.072)	(0.072)	(9.151E-04)	(9.342E-04)	(9.343E-04)
AGE	0.613***	0.487***	0.478***	3.915E-03***	2.774E-03*	2.658E-03*
	(0.113)	(0.113)	(0.113)	(1.472E-03)	(1.484E-03)	(1.484E-03)
STATE	2.038***	2.225***	2.182***	2.255E-02***	2.490E-02***	2.445E-02***
	(0.251)	(0.254)	(0.254)	(3.240E-03)	(3.297E-03)	(3.295E-03)
NONCON	-1.883***	-1.731***	-1.687***	-2.158E-02***	-2.026E-02***	-1.977E-02***
	(0.206)	(0.205)	(0.205)	(2.678E-03)	(2.687E-03)	(2.688E-03)
EXPORT	-1.933***	-1.820***	-1.762***	-2.202E-02***	-2.136E-02***	-2.067E-02***
	(0.267)	(0.267)	(0.267)	(3.514E-03)	(3.538E-03)	(3.539E-03)
POP	0.556***	0.012	0.195	8.560E-03***	3.476E-03*	5.653E-03***
	(0.133)	(0.142)	(0.145)	(1.745E-03)	(1.867E-03)	(1.919E-03)
DIVERSITY	1.417	1.184	1.361	1.739E-02	1.456E-02	1.689E-02
	(1.475)	(1.465)	(1.468)	(1.908E-02)	(1.907E-02)	(1.914E-02)
HUMAN	0.388***	0.324***	0.307***	4.244E-03***	3.687E-03***	3.472E-03***
	(0.078)	(0.078)	(0.078)	(1.022E-03)	(1.033E-03)	(1.035E-03)
INDRD	0.742***	0.752***	0.779***	8.801E-03***	8.984E-03***	9.298E-03***
	(0.056)	(0.057)	(0.057)	(7.377E-04)	(7.443E-04)	(7.457E-04)
COMP	0.335***	0.691***	0.487***	5.007E-03***	8.019E-03***	5.658E-03***
	(0.084)	(0.091)	(0.098)	(1.080E-03)	(1.187E-03)	(1.274E-03)
Industry fixed effect	No	Yes	Yes	No	Yes	Yes
Total obs.	12933	12933	12933	12933	12933	12933
Uncensored obs.	4373	4373	4373	4373	4373	4373
LR χ^2	1982.27	2115.36	2149.57	1151.45	1223.76	1251.3
Log likelihood	-19219.77	-19153.228	-19136.124	557.889	594.043	607.810

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses.

Column 3 and Column 6 of Table 2.2 show the estimates of Eq.4. I report the marginal effects of the interaction term based on calculation using delta method rather than the estimated coefficients. This is because that the coefficient of the interaction term does not reflect the real interaction effect in nonlinear models. The real interaction effect is jointly decided by the coefficients of technological similarity index, localization and the interaction term, value of localization variable and technological similarity index, and standard normal cumulative distribution of the latent variable. My results reveal that adding the interactive term affect neither the sign nor the significance level of the localization and technological similarity index variables and that the marginal effect of the interactive term between localization agglomeration and technological similarity has a significant and negative relationship with R&D investment, as expected. I interpret the negative sign of the interactive term as follows: the negative effect of knowledge spillover on firm’s R&D investment increases with localization agglomeration. In other words, localization agglomeration augments the negative impact of knowledge spillover on firm’s R&D investment. More specifically, my estimates show non-trivia marginal effect of localization on the relationship. When industrial employment increases from 10,000 to 20,000, a 0.01 increase of technological similarity index would cause a firm to reduce 0.18% more in R&D investment, and 0.00002 more in R&D intensity.

The model yields expected coefficients for the control variables. Theoretically, R&D investment varies with a firm’s accessibility to funding resources and operation management (i.e. the capability of risk diversification). Firm size is one common indicator of firm’s financial capacity and risk-spread ability (Smith et al., 2002). Big firms have adequate financial resources to invest in R&D and strong financial capacity to spread risks associated with unsuccessful R&D investment. Firm age is another widely-used indicator of firm’s accessibility to external funding and capability of risk diversification. Older (long-survived) firms usually with more stable funding stream and more successful experience of risk aversion are more likely to invest more in R&D activities than younger ones.

As expected, the regression results show that R&D investment is positively correlated with both firm size and firm age at 1% significance level.

Firms' ownership also significantly influences their decisions on R&D investments. I find that state-owned enterprises have consistently higher R&D investment than non-state-owned domestic firms, while foreign-owned firms and non-continental Chinese firms present lowest R&D input level. State-owned firms that are considered by the central government as the lifelines of national economy receive numerous funding for R&D to promote their technological competence. On the opposite, foreign-owned firms and non-continental Chinese firms produce and assemble products in mainland China to take advantage of cheap labor force. They are more likely to set up R&D facilities and direct their R&D investment in their home country or region. A firm's R&D investment decreases when the share of its exported goods increases. Given China's position in the value chain of international trade at the time, most of the export products are either assembled high-tech equipment or low-end commodities, neither of which requires high-level technological innovations.

The positive coefficient of *INDRD* suggests that firms increase R&D investment when R&D investment of neighboring firms is high. This can be interpreted as evidence of R&D incentive brought by peer competition. One can also interpret *INDRD* as the cost of research and development. More industry R&D in a city might suggest that the cost of R&D in that city is cheaper. For instance, firms have a larger chance to share R&D labs and equipment if a city has bigger R&D base in that given industry. When the marginal effect on outputs of R&D investment is larger than the marginal effect on outputs of other factors (labor, land, other capital), firms would have much stronger incentive to make R&D investment.

I find a positive impact of competition. This result is consistent with Glaeser, et al. (1992) and in favor of Porter and Jacob's theory that competition encourages innovation. One can also take the view that smaller firms bring more entrepreneurship with stronger R&D intention.

My results indicate that firms invest more R&D in larger cities. This is consistent with the theoretic prediction. Big cities generate big market demand that supports the experiment of new ideas and products. Although industry diversity is argued to facilitate cross-industry spillover (Jacobs, 1969), I find no evidence that it influences firm's R&D investment. Finally, firm's R&D investment is found high in cities with rich human capital.

2.5.2 Robustness Check

Estimation problems may present when there are omitted variables and/or there is an endogenous issue. For instance, unobserved local industry policy may affect agglomeration, technological similarity, and R&D investment simultaneously. A way to correctly estimate biases is to run a two-step Tobit regression. I use instrument variables defined by using time-lag data. Data generating the instrument variables is drawn from China Economic Census 2004 (CES2004). The dataset includes all individual firms in China in 2004. Industry employment, technological similarity index and their interaction terms computed using CES2004 data are applied to instrument the three key variables in the basic estimation.

Table 2.3 Two-Step Estimator Agglomeration and Firm R&D Expenditure

	Dependent variable: RD		Dependent variable: RDI	
	(1)	(2)	(3)	(4)
TS	-3.099***	-3.178***	-3.981E-02***	-4.291E-02***
	(0.649)	(0.423)	(8.513E-03)	(5.957E-03)
LOC	-0.956***	-0.659***	-1.221E-02***	-8.951E-03***
	(0.117)	(0.068)	(1.539E-03)	(9.616E-04)
LOC×TS		-1.112***		-1.488E-02***
		(0.191)		(2.714E-03)
SIZE	2.164***	2.160***	1.501E-02***	1.496E-02***
	(0.072)	(0.072)	(9.352E-04)	(9.353E-04)
AGE	0.485***	0.472***	2.752E-03*	2.563E-03*
	(0.113)	(0.113)	(1.485E-03)	(1.484E-03)
STATE	2.204***	2.168***	2.463E-02***	2.421E-02***
	(0.254)	(0.254)	(3.302E-03)	(3.300E-03)
NONCON	-1.717***	-1.670***	-2.008E-02***	-1.952E-02***
	(0.205)	(0.205)	(2.690E-03)	(2.691E-03)
EXPORT	-1.797***	-1.751***	-2.108E-02***	-2.052E-02***
	(0.268)	(0.268)	(3.544E-03)	(3.545E-03)
POP	0.054	0.255*	3.953E-03**	6.465E-03***
	(0.147)	(0.151)	(1.931E-03)	(1.995E-03)
DIVERSITY	1.352	1.321	1.671E-02	1.645E-02
	(1.470)	(1.474)	(1.913E-02)	(1.921E-02)
HUMAN	0.295***	0.320***	3.299E-03***	3.626E-03***
	(0.079)	(0.080)	(1.047E-03)	(1.060E-03)
INDRD	0.797***	0.767***	9.568E-03***	9.185E-03***
	(0.062)	(0.062)	(8.088E-04)	(8.162E-04)
COMP	0.682***	0.378***	7.974E-03***	4.178E-03***
	(0.093)	(0.108)	(1.214E-03)	(1.411E-03)
Industry fixed effect	Yes	Yes	Yes	Yes
Total obs.	12933	12933	12933	12933
Uncensored obs.	4373	4373	4373	4373
Wald χ^2	1878.19	1902.25	1068.66	1091.7
Wald test of exogeneity	7.2	11.61	9.19	16.6
P-value of Wald test	0.0273	0.0088	0.0101	0.0009

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses.

Table 2.3 presents the results of the two-step Tobit estimation. The estimated coefficients/marginal effects of localization, technological similarity and their interaction term are consistently negative and significant as in the basic estimation. The two-step estimator even suggests a stronger influence of localization and knowledge spillover on firm's R&D choice. Based on Column 2 and Column 4 of Table 2.3, the estimated coefficient of localization is about 7%

larger in absolute value in two-step Tobit estimation than in the basic estimation. The coefficients of technological similarity and the interaction term have even larger differences, more than 20% and 45% in absolute value respectively, between the two estimations. This indicates the negative impact of knowledge spillover and the conditional effect of localization on spillover's impact on R&D is quite robust.

Table 2.4 presents results, by sample size (above and below median-size firms, respectively), for both Tobit and two-step Tobit estimates with industry fixed effect. Interpreting the results leads us to two conclusions. The first conclusion is that my estimates are robust. All key variables (knowledge spillover, localization agglomeration, and the interaction term of those two) have significant and expected (negative) signs at 5% significance level or better. The second conclusion is that firm size matters. Using the full sample as the reference, the estimated value of the coefficient of technological similarity suggests that the negative impact of knowledge spillover on R&D investment decreases for the above median-size firms, and increases for the below median-size firms. For instance, the elasticity of technological similarity on latent R&D spending variable decreases to -1.033 and increase to -2.041, from -1.523, for the above and below median-size firms, respectively (Column 3 in Table 2.4 and Column 1 in Table 2.3). I obtain the similar results by using RDI as the dependent variable. The conclusion holds for the results from Eq. 4 as well for the two-step Tobit estimator. The changing pattern of the value of the interactive term follows the pattern of the technological similarity variable. The estimated value of the coefficient reveals that the negative impact of localization agglomeration on the negative relationship between firm's R&D and knowledge spillover decreases for the above median-size firms and increase for the below median-size firms. Again, the changing pattern holds by using RDI. The differences of the estimated coefficients between sub-samples by size (of technological similarity and the interactive term) are substantial. For instance, the estimated coefficient of technological similarity is about 68% larger in absolute value for below median-size firms than for above median-size firms. The difference in the estimated coefficient of the interactive term is in the same range of percentage change.

The differences in the key variables' estimation by sample size may explain the micro-foundation of the negative effect of knowledge spillover on firm's R&D investment. Big firms are not always technological leaders, but they always undertake the majority share of R&D inputs (Scherer, 1992). When co-locating with small firms, the knowledge spillover from big firms to small firms should be higher than the knowledge spillover from small firms to big firms. The asymmetry knowledge spillover would become severer as the number of co-located small firms increases. The knowledge expropriation assumption suggests that the return to R&D investment of big firms would be less if they locate in cities characterized by larger localization agglomeration (which contains more small firms). Big firms in those more locally agglomerated cities should have stronger motivation to reduce their R&D effort. Therefore, my results suggest the cost-saving effect for the negative relation between knowledge spillover and firm's R&D investment. My results are in line with Acs, Audretsch and Feldman (1994) who speculate small enterprises exploit external knowledge, especially those created by universities and large corporations, in producing innovative outputs.

Table 2.4 Agglomeration and R&D Investment by Firm Size[19]

	Dependent variable: RD				Dependent variable: RDI			
	Tobit		Two-Step		Tobit		Two-Step	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Above median-size firms				
TS	-1.888***	-2.252***	-2.103**	-2.413***	-1.358E-02**	-2.167E-02***	-1.772E-02**	-2.368E-02***
	(0.731)	(0.525)	(0.897)	(0.582)	(6.784E-03)	(5.224E-03)	(8.338E-03)	(5.744E-03)
LOC	-0.809***	-0.579***	-0.776***	-0.544***	-8.152E-03***	-6.269E-03***	-8.222E-03***	-6.011E-03***
	(0.124)	(0.078)	(0.153)	(0.090)	(1.154E-03)	(7.726E-04)	(1.424E-03)	(8.874E-04)
LOC×TS		-0.599***		-0.865***		-6.820E-03***		-9.303E-03***
		(0.162)		(0.257)		(1.665E-03)		(2.590E-03)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	6433	6433	6433	6433	6433	6433	6433	6433
Uncensored obs.	2661	2661	2661	2661	2661	2661	2661	2661
LR χ^2	1197.57	1210.55			797.56	814.02		
Log likelihood	-11148.659	-11142.17			1756.192	1764.422		
Wald χ2			1088.37	1097.45			701.97	713.98
Wald test of exogeneity			0.46	3.27			0.78	2.51
P-value of Wald test			0.793	0.3515			0.679	0.4738
				B. Below median-size firms				
TS	-2.756***	-3.188***	-4.154***	-4.044***	-4.349E-02***	-5.078E-02***	-6.912E-02***	-6.830E-02***
	(0.855)	(0.586)	(0.969)	(0.636)	(1.486E-02)	(1.075E-02)	(1.686E-02)	(1.164E-02)
LOC	-0.866***	-0.637***	-1.129***	-0.775***	-1.432E-02***	-1.077E-02***	-1.807E-02***	-1.302E-02***
	(0.164)	(0.098)	(0.186)	(0.108)	(2.846E-03)	(1.795E-03)	(3.228E-03)	(1.976E-03)
LOC×TS		-1.035***		-1.451***		-1.576E-02***		-2.353E-02***
		(0.209)		(0.300)		(3.812E-03)		(5.497E-03)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	6500	6500	6500	6500	6500	6500	6500	6500
Uncensored obs.	1712	1712	1712	1712	1712	1712	1712	1712
LR χ2	502.08	526.36			413.73	430.46		
Log likelihood	-7978.900	-7966.758			-701.210	-692.844		
Wald χ2			450.9	467.6			377.97	390.72
Wald test of exogeneity			19.09	23.46			17.28	25.72
P-value of Wald test			0.000	0.000			0.000	0.000

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses.

I further examine how the impact of localization agglomeration and knowledge spillover on R&D effort varies between firms that launched new products in 2007 and those did not. For a given period, firms that launch new products are likely to be technologically advanced than their counterparts and might face a higher risk of knowledge expropriation in localization agglomeration (Jo and Lee, 2014). If expropriation-avoidance effect dominates the reduction in R&D investment, I should expect a stronger negative effect of localization agglomeration and technological similarity on firms launched new products. The estimation results in Table 2.5, however, show localization and technological similarity have much weaker impacts on R&D spending and R&D intensity for firms that launched new products. When applying two-step Tobit estimator, Column 4 and Column 8 of Table 2.5 show the coefficients/marginal effects of localization and the interactive term are no longer significant for firms launched new products. The coefficient of technological similarity for firms launched new products is significant, however, the magnitude is much smaller than the coefficient of technological similarity for firms did not launch new products. In specific, the coefficient for the latter is 4.3 times and 1.3 times larger using R&D spending and R&D intensity as dependent variable respectively. It suggests the decrease in firm R&D investment caused by expropriation-avoidance is possibly quite limited. Rather the finding indicates the flow of product R&D is slower than the flow of process R&D. Technological leaders may achieve high knowledge appropriability from their R&D investment as technological laggards do not have the baseline knowledge and skills to identify, absorb or benefit from the novel technologies and knowledge of technological leaders (Cohen and Levinthal, 1990; Shefer and Frenkel, 1998; McEvily and Chakravarthy, 2002; Cassiman and Veugelers, 2005).

Table 2.5 Agglomeration and R&D Investment by New Product Production

	Dependent variable: RD				Dependent variable: RDI			
	Tobit		Two-Step		Tobit		Two-Step	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. New products lauched in 2007				
TS	-1.327*	-0.897***	-1.809**	-0.964**	-2.272E-02	-2.060E-02**	-3.713E-02**	-2.812E-02***
	(0.686)	(0.338)	(0.821)	(0.379)	(1.465E-02)	(9.571E-03)	(1.752E-02)	(1.068E-02)
LOC	-0.174	-0.122**	-0.128	-0.081	-3.835E-03	-3.261E-03**	-3.147E-03	-2.770E-03
	(0.127)	(0.058)	(0.155)	(0.068)	(2.723E-03)	(1.650E-03)	(3.319E-03)	(1.921E-03)
LOC×TS		-0.224*		-0.209		-5.270E-03		-7.656E-03
		(0.120)		(0.180)		(3.384E-03)		(5.168E-03)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	2861	2861	2861	2861	2861	2861	2861	2861
Uncensored obs.	1894	1894	1894	1894	1894	1894	1894	1894
LR $\chi2$	520.15	523.57			200.03	202.37		
Log likelihood	-6591.143	-6589.435			984.084	985.253		
Wald $\chi2$			536.81	539.01			196.51	198.66
Wald test of exogeneity			1.96	1.99			3.03	3.55
P-value of Wald test			0.376	0.5755			0.220	0.3141
				B. No new products lauched in 2007				
TS	-2.635***	-3.337***	-3.491***	-4.111***	-2.107E-02***	-3.088E-02***	-2.972E-02***	-3.833E-02***
	(0.760)	(0.577)	(0.892)	(0.626)	(7.090E-03)	(5.703E-03)	(8.336E-03)	(6.158E-03)
LOC	-0.585***	-0.525***	-0.628***	-0.537***	-6.117E-03***	-5.568E-03***	-6.823E-03***	-5.812E-03***
	(0.135)	(0.088)	(0.160)	(0.098)	(1.261E-03)	(8.665E-04)	(1.496E-03)	(9.643E-04)
LOC×TS		-0.900***		-1.413***		-8.947E-03***		-1.375E-02***
		(0.181)		(0.271)		(1.794E-03)		(2.681E-03)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	10072	10072	10072	10072	10072	10072	10072	10072
Uncensored obs.	2479	2479	2479	2479	2479	2479	2479	2479
LR $\chi2$	931.17	955.86			595.25	620.07		
Log likelihood	-11820.362	-11808.015			182.730	195.142		
Wald $\chi2$			801.78	821			519.24	540.5
Wald test of exogeneity			3.44	10.98			4.25	10.89
P-value of Wald test			0.179	0.0118			0.120	0.0123

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses.

2.6 Conclusion and Policy Implication

To build an innovative economy has become the goal of an increasing number of countries and regions. However, public policies could not efficiently promote and channel the innovation of private sector without fully understanding how firms are involved in the production of knowledge. Previous research reveals both external and internal R&D investment contribute to the knowledge creation of firms. This essay takes one more step to show that firms would take advantage of external knowledge and save self-financing R&D investment. As knowledge spillover is localized, firm's R&D investment reduction presents a geographic pattern: firms reduce more in R&D in locations characterized by greater localization agglomeration. The idea is demonstrated by a simple Cournot type, two-stage competition model which theoretically shows localization strengthens spillover effect on firms' R&D reduction. Empirical examination on Chinese high-tech firms verifies the theoretic predictions. Evidence based on subsample regression further reveal the negative impact is more due to the cost-saving effect than the expropriation-avoidance effect. The findings coincide well with agglomeration theory that firms form clusters to benefit from a general pool of public knowledge. The benefit from knowledge spillover is quite considerable since a firm could achieve big innovative outputs with little R&D inputs (Bagella and Becchetti, 2002).

The essay provides several policy implications. First, public policy and planning should facilitate the spatial concentration of economic activities to promote knowledge transmission since it saves firm's R&D investment. One of the options for concentrated development is to build industrial parks. Originated from developed countries, industrial park development is now also advocated in developing countries like China and India (Ding and Zhao, 2011). Industrial parks are usually built at places outside main residential area and with good transportation access. It is argued that this kind of land and industrial development provides benefits include concentrating dedicated infrastructure to reduce average expense of infrastructure usage, increasing attractiveness to new business by providing integrated infrastructures, targeting industrial preferential policies, reducing environmental and social impact of industrial uses, and localizing environmental controls with specific needs of an industrial. This essay suggests one more benefit of industrial parks as facilitating knowledge spillover and saving firm R&D cost.

The advocacy of industrial park development, however, does not suggest every city and place is suitable to set up industrial parks. Studies show, in China, local governments set up too many industrial parks that on average each prefecture city has more than 20 industrial parks. Some of those industrial parks are located at remote villages with below average transportation accessibility. To attract business, those otherwise uncompetitive parks typically offer low land and rent cost. While the firms temporarily are attracted to those parks, they leave for other industrial parks after seizing advantages from local governments. This essay indicates the distortion on firm location choice by industrial park policies not only reduces local governments' fiscal revenue but also impedes agglomeration economy to work at its best. At least for R&D investment, firms benefit less due to the segregation of production caused by oversupply of industrial parks.

A related implication is that local governments should differentiate specialization of industries. It has been criticized in China that local governments compete in the development of every industry and form an indifferent industry structure. While the findings of this essay suggest benefit from industry differentiation; the larger the concentration of an industry, the more saving firms could achieve in R&D investment in that industry. Collaborated development of local governments with differentiate industrial specialization can increase the overall welfare of the society.

Since knowledge spillover relies heavily on firm/worker interaction, local government could serve to connect firms with similar technologies through forum, contest and other format of events. Although these activities traditionally are carried out by industrial organizations, government engagement might be important for promoting the quality and efficiency of the activities in developing countries like China as local governments there have the determining force on firm development.

The findings of the first essay also point to the direction of R&D preferential policies. Currently, Chinese governments provide tax incentives for all high-tech firms to encourage their R&D investment. However, this essay shows governments should focus on impelling firms' R&D activities in new product development as they could hardly freeride from neighboring firms' R&D investment.

Finally, policies, at all levels, must promote human capital level and industry competition to encourage R&D investment. There is still a big gap between China's education expense and that of developed countries. In 2014, China's education expense was 3.8% of national GDP, lower than 5.4% of the U.S. and 5.1% of EU-25 countries. China's central, provincial, and prefectural governments should all invest more intensively in education, providing government funded training program and mandating firms to increase training expense. Governments should also commit to reduce local monopoly. Although monopoly limits external knowledge flows and gives some incentives for monopoly firms conducting R&D, it hurts the innovation motivation of all the other firms.

Chapter 3: Agglomeration and Firm Survival

3.1 Introduction

It has been long established in the literature that there are certain benefits associated with urban agglomeration. The aggregated demand derived from concentration allows firms to bring down the cost of acquiring intermediate goods and infrastructure (Puga, 2010). Meanwhile, the proximity between firms facilitates interfirm labor mobility and knowledge exchange (Glaeser et al., 1992; De Silva and McComb, 2012). These agglomerative externalities could be realized within the same industry (Marshall externalities), or across industries (Jacob externalities). Both types of agglomeration externalities encourage the concentration of new firms (Rosenthal and Strange, 2003; Niu et al., 2015). One would expect to see a better post-entry performance of new firms if agglomeration only delivers advantages to them. Empirical evidence, indeed, reveals firms that are located in big cities or clusters, on average have higher productivity than firms in small cities or periphery.

The higher productivity, however, might be achieved through the elimination of less-productive firms. The geographic concentration of firms, according to Melitz and Ottaviano (2008), increases the “toughness” of competition and creates more hazard for less-productive firms. The process of eliminating less-productive firms in dense markets is known as the firm selection effect (Melitz, 2003), which has been empirically proved to be another key contributing factor to the productivity advantage of big cities in addition to agglomeration externalities (Saito and Gopinath, 2009;

Comes et al., 2012; Accetturo et al., 2013). This suggests firms in dense markets may not have the advantage of survival. Yet, empirical studies have not reached a consensus conclusion regarding the impact of agglomeration on firm survival. The evidence is particularly confusing as previous studies focused on different types or attributes of agglomeration (Wennberg and Lindqvist, 2010).

Under industry scope, agglomeration is further distinguished into localization or urbanization, both emphasizing the scale effect of agglomeration. There is another way to address agglomeration under industry scope with a focus on its structure, that is the specialization and diversity of agglomeration. Localization and specialization are related to the impact of own industry concentration, while urbanization and diversity are associated with the impact of all/other industry concentration. The sources and strength of agglomeration externalities are not the same for localization, urbanization, specialization and diversity (Rosenthal and Strange, 2004), which means they may play different roles in firm survival.

This essay seeks to answer the questions of whether agglomeration affects firm survival and whether the impact varies by the attributes or types of agglomeration with new empirical evidence. To do so, I study the survival of new entrants in five industries based upon firm-level data from Maryland. The impacts of localization, urbanization, specialization and diversity are examined separately. In addition, this essay examines the role of employment centers in supporting firm survival. Agglomerative economies are the main forces behind the formation and evolution of employment centers. While the literature documents a uniquely positive impact of employment centers on firm birth, it will be interesting to see if they support survival as well. The results show firms in all five industries face higher level of hazards and survive for shorter periods of time when they are proximate to bigger urbanization agglomeration. In contrast, localization, specialization, diversity and employment centers prolong the life of mature firms in some industries.

The rest of the essay proceeds as follows. Section 2 reviews the literature on firm survival. Section 3 introduces methodology, data and variables. Section 4 presents regression results with discussion. And Section 5 concludes the essay with policy implications.

3.2 Literature Review

Firm survival has been intensively studied in the field of industry organization. Key determinants have been identified including, but not limited to, firm size, human capital, capital intensity, age and innovation rate, etc. (Evans 1987; Dunne and Samuelson 1988, 1989; Audretsch 1991; Audretsch and Mahmood 1995). Most of these factors reflect firms' abilities to acquire resources for production or recover from idiosyncratic shocks.

The spatial exploration on firm survival determinants is more recent. The sharing, matching and transferring of resources and information in concentration could improve survival opportunity. Especially for new entrants, co-locating with incumbent firms offers "the constant market for skill", enhances attractiveness to employees, provides chances to 'comparing shopping', and connects them to market information, industrial knowledge and development strategy, of which all are crucial for their long-run business success (Maskell, 2001).

Yet, all the advantages of geographic concentration on firm survival could be offset by agglomeration diseconomy. Agglomeration leads to high rent costs, wage rates, commuting costs, as well as the other negative externalities (Richardson, 1995; Folta et al. 2006), which might jeopardize firm survival. In addition, geographic concentration creates more intense competition in the product market and much smaller price-cost margins that make survival even difficult for firms in larger and denser areas (Syverson, 2004; Melitz and Ottaviano, 2008). As argued by Asplund and Nocke (2006), big cities are more productive because competition makes the efficiency of marginal surviving firms in large markets exceeds those in small markets. Theoretically, if agglomeration economy outweighs agglomeration diseconomy, firms in concentration should have a lower turnover rate than those in the periphery. On the contrary, if agglomeration diseconomy is larger, geographic concentration would lead to a higher mortality rate. Since agglomeration diseconomies get stronger as concentration grows and matures (Beaudry and Swann, 2001; Folta et al. 2006), there should present a stronger firm selection effect and an increased mortality rate in larger concentration.

Empirical studies seem to support a negative role of geographic concentration in firm survival by examining urban and rural firm survival. Strotmann (2007) and Huiban (2011) report firms experience a lower survival chance in urban areas than in rural areas respectively in Germany and France. A similar survival pattern is also revealed in the United States (Buss and Lin, 1990; Stearns et al., 1995; Falck, 2007; Plummer and Headd, 2008; Yu et al., 2009). One exception is Fotopoulos and Louri (2000) who report manufacturing firms in Greece have a higher survival rate in densely populated Greater Athens than the rest of the country. However, the "cherry-pick" of Greater Athens as the study area may cause endogeneity problem: as the primary city in Greece, Greater Athens offers many other vital resources for firm survival besides agglomeration economy. For example, the access to the country's core political power in Greater Athens overwhelms most factors in impacting on firm performance. Renski (2008) investigates firm survival through a continuum of locations from nonmetropolitan rural to urban core and identifies a bell-shaped survival opportunity. Survival rate rises when moving from rural areas to suburbs and small cities but then plummets to the nadir at urban core. Renski's study indicates moderate concentration is favorable for firm survival, while heavy concentration becomes hazardous.

It has been discussed that agglomeration economies may vary on the margin between the agglomeration within and across industries. For instance, localization is found to be more prominent than urbanization in promoting firm birth and productivity (Henderson, 2003; Rosenthal and Strange, 2003). One explanation for this divergence might be the matching of skills and spillover of knowledge are easier to achieve between firms within the same industry as they share closer production technologies (Jaffe, 1986; Strange et al., 2006). It is more likely that agglomeration economies stem from the concentration of kinship firms neutralize or overwhelm the diseconomies of concentration. This suggests localization and specialization are expected to have a high possibility of supporting firm survival. In contrast, urbanization is more likely to show a negative impact since it generates less agglomeration economy and more captures the intense competition from the overall scale of agglomeration. If there are benefits associated with the concentration of different industries on survival, it would be more likely to be represented by agglomerative diversity (Renski, 2010). Diversity facilitates cross-industry knowledge spillover and creates a more stable market demand by ironing out random shocks to individual industries.

Studies that separately investigate localization, urbanization, specialization and diversity reveal their different impacts on firm survival. No matter measured by employment or population, urbanization agglomeration always presents negative impact (Sorenson and Audia, 2000; Renski, 2010; Neffke et al., 2012). While the impact of diversity is predicted to be positive in Acs et al. (2007) and Renski (2010), but negative in De Silva and McComb (2012). The effect of own industry concentration varies by geographical aggregation. Folta et al. (2006) find at the metropolitan level, larger clusters of same industry challenge survival, at least for American biotechnology firms. Acs et al. (2007) focus on service firms and find a negative impact of localization at Labor Market Area level. However, the role of own industry concentration in firm survival reverses when it is measured at smaller geographic units. Pe'er and Vertinsky (2006) show that within a twenty-mile buffer of manufacturing plants, localization agglomeration is positively associated with survival. The positive impact is also reported by Wennberg and Lindqvist (2010) and by Renski (2010) through a multiple ring examination. In their studies, the concentration of own industry is measured by specialization indicators (which are industry employment share and location quotient respectively). De Silva and McComb (2012) study both specialization (measured by location quotient) and localization (measured by the number of rival firms) and find they accelerate firm turnover within one-mile radius of a plant, but reduce mortality rate beyond that distance. These contradictory findings suggest that more empirical evidence regarding the impacts of different types and attributes of agglomeration should be provided.

Undoubtedly, weak firms with heavier dependence on external resources to realize their business successes tend to be attracted to bigger agglomerations. For instance, Shaver and Flyer (2000) argue firms with the weakest technologies, human capital, training programs, suppliers, or distributors have the strongest intention to locate in economic clusters. (However, the benefits of agglomeration externalities from concentration still do not keep weak firms from dying earlier in the competition with stronger firms. Thus, if there is a disproportionately high share of weak firms in denser markets, the negative impact of agglomeration on survival could be overestimated. To address such selection bias, De Silva and McComb (2012) investigate the survival performance of high-tech firms which have been in business for at least three years. They assume most weak firms fail in their early years and the remaining incumbent firms have demonstrated some degree of sustainability. They are still able to find a statistically significant impact of concentration by only keeping the mature firms. Yet, one concern is raised for the focus of high-tech firms. Those aging high-tech firms can also be weak, to some extent, if they do not update their technologies in time. The selection examination should be applied to other industries to further clarify the disturbance of the overpopulation of weak firms.

3.3 Research Design

3.3.1 Measuring Geographic Concentration

Agglomeration impact attenuates rapidly with the increase of distance to firm location (Rosenthal and Strange, 2003; 2005). On firm survival, the distant concentration of firms presents much milder impact compared to firms' neighboring concentration (Renski, 2010; De Silva and McComb, 2012). Considering the diminishing trend of agglomeration impact by distance, I create one-mile and five-mile buffers around the actual location of firms and measure specialization, urbanization and diversity within each buffer. Specialization rather than localization is applied to measure Marshall externalities because most previous studies test Marshall externalities using specialization at smaller geographic units and it captures a net impact of own industry concentration (Rosenthal and Strange, 2004). A firm's self-employment is excluded from the calculation of agglomeration indicators. Location quotient of industry employment is applied as an indicator of specialization. It is calculated as $LQ_{ijk} = \frac{E_{ijk}/E_{ik}}{E_{ij}/E_i}$, where E_{ijk} denotes the number of workers in industry j in buffer k, E_{ik} denotes the number of workers in all industries in buffer k, E_{ij} denotes the number of workers in industry j in Maryland, and E_i denotes the number of workers in all industries in Maryland. And diversity is proxied by $1 - \sum_j^n {S_{ijk}}^2$, where S_{ijk} denotes the employment share of industry j in buffer k and $\sum_j^n {S_{ijk}}^2$ is the Herfindahl-Hirschman Index. Total employment (in log form) within a specific buffer is adopted to present urbanization agglomeration level.

Agglomeration economies help the formation of employment centers and economic clusters. These centers or clusters, in turn, provide unique benefits on economic activities. When controlling other agglomeration attributes, the higher density of employment centers may accelerate the process of sharing, matching and learning.[20] This suggests employment centers might have a unique positive effect on firm survival as they do on firm birth. The employment centers in Maryland are defined based on functional geographic units in line with Giulinao and Small (1991) as continuous dense areas that meet specific employment and density thresholds. In specific, this essay applies Traffic Analysis Zones (TAZs) as functional geographic units for center generation. There are 4058 TAZs in Maryland, each of which shares the same number of annual trips. By aggregating employment data into TAZs, I first find core spots with employment density higher than eight workers per acre (therefore set as the density threshold). Adjacent TAZs are incorporated if they have at least six workers per acre. Aggregately, the density of the continuous areas (core spots plus their adjacent TAZs) should be kept above the density threshold. I then adjust the combination of TAZs based on geographic endowments and transportation network, and define those continuous TAZs as an employment center if they jointly have at least 10,000 workers with employment density higher than eight workers per acre. Given the presence of economic fluctuation during my study period, only peak employment and density of TAZs are used for identification. Once a center is set up, its boundary is fixed for the entire period. Following this approach, I identify 19 employment centers in Maryland as shown in Figure 3.1 and Table 3.1. Most of them concentrate in the corridor counties between Washington D. C. and Baltimore City. Together, these centers cover about 40% of jobs in Maryland but occupy less than 0.8% of land area.

[20] Suppose two firms face identical concentration within five-mile buffer to their location except the distribution of economic activities. For the first one, employment evenly spreads out in the five-mile buffer area; for the second one, all employment concentrates within one mile to the firm. Since agglomeration theory is almost entirely concerned with density (Rosenthal and Strange. 2004), the second one should generate a stronger agglomeration effect although the two five-mile buffers have the same employment size and average density at five-mile buffer area.

The average employment density in these centers is about 20 workers per acre that is 50 times higher than the state average. A dummy variable is used to distinguish the born location of new firms, which equals 1 if a firm was born in employment centers and 0 if not. Similar employment centers in Maryland are defined and applied in Niu et al. (2015) which find a positive relationship between employment centers and firm birth. It is worth checking how employment centers affect the death of new entrants in this essay.

3.3.2 Model

The impact of geographic concentration on new firms' survival is examined by using the semiparametric Cox proportional hazard model. The Cox model has become the standard method for firm survival study since it requires less than complete distributional specification (Cameron and Trivedi, 2005). The convenience in model specification and easiness in coefficient interpretation make Cox model the most widely used model in survival analysis. It can be expressed by:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t | T \ge t)}{\Delta t} \tag{1}$$

where the hazard rate $h(t)$ is the possibility that a firm fails in the next instant if it survives to period t. A higher hazard rate is equivalent to a lower survival chance. A standard Cox model can be rewritten as the composite of two separate functions as:

$$h(t) = h_0(t) \exp(x'\beta) \tag{2}$$

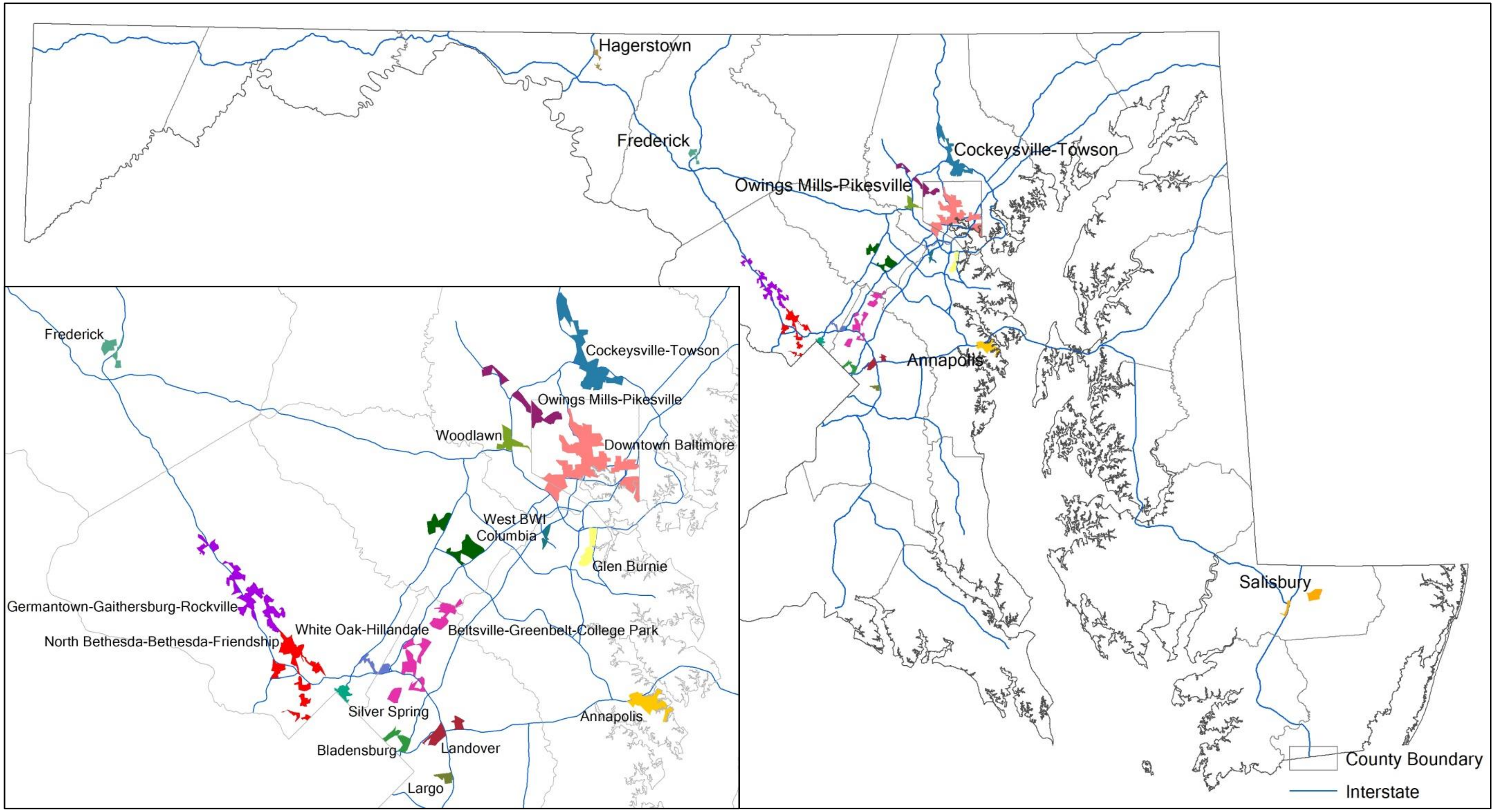

Figure 3.1 Employment Centers in Maryland

Table 3.1 Characteristics of Employment Centers in Maryland

Employment center	Area (acres)	Employment	Density	Diversity index
Downtown Baltimore	13659.33	346554	25.37	10.17
		(18028)	(1.32)	(0.26)
North Bethesda-Bethesda-Friendship	4924.50	197973	40.20	9.34
		(8628)	(1.75)	(1.49)
Germantown-Gaithersburg-Rockville	5872.89	129177	22.00	8.92
		(16793)	(2.86)	(0.62)
Cockeysville-Towson	7015.18	112102	15.98	10.96
		(5834)	(0.83)	(0.41)
Beltsville-Greenbelt-College Park	5558.63	70173	12.62	9.44
		(6889)	(1.24)	(1.46)
Columbia	3641.06	46271	12.71	9.84
		(9956)	(2.73)	(0.94)
Annapolis	3061.69	41313	13.49	9.10
		(3395)	(1.11)	(0.44)
Woodlawn	1579.13	40378	25.57	3.24
		(3420)	(2.17)	(0.52)
Owings Mills-Pikesville	3507.94	38315	10.92	8.94
		(2257)	(0.64)	(1.00)
Silver Spring	793.79	30743	38.73	7.92
		(4476)	(5.64)	(0.46)
Salisbury	2966.73	29598	9.98	1.99
		(1376)	(0.46)	(0.15)
Landover	1758.29	22927	13.04	8.97
		(2753)	(1.57)	(0.71)
Frederick	1306.17	18870	14.45	4.50
		(4723)	(3.62)	(0.66)
Hagerstown	1047.81	15351	14.65	6.44
		(1418)	(1.35)	(1.27)
Glen Burnie	1583.49	14775	9.33	6.43
		(1584)	(1.00)	(0.85)
Bladensburg	1211.43	13270	10.95	6.26
		(2680)	(2.21)	(1.08)
West BWI	514.36	11801	22.94	2.25
		(9133)	(17.76)	(1.57)
White Oak-Hillandale	939.31	11778	12.54	4.35
		(2399)	(2.55)	(0.89)
Largo	639.48	10703	16.74	5.16
		(926)	(1.45)	(0.90)

Standard errors are in parentheses.

where the hazard rate $h(t)$ is the possibility that a firm fails in the next instant if it survives to period t. A higher hazard rate is equivalent to a lower survival chance. A standard Cox model can be rewritten as the composite of two separate functions as:

$$h(t) = h_0(t)\exp(x'\beta) \quad (2)$$

where $h_0(t)$ is the unspecified baseline function contains only the age of a firm. x is a vector of agglomeration indicators and control variables, so $\exp(x'\beta)$ captures location-specific and firm-specific features that are assumed to affect hazard rate. The exponential form of the second function allows coefficients to be easily interpreted. For instance, if the jth regressor increases by one unit and other covariates remain unchanged, the new hazard will be $\exp(\beta_j)$ times the original hazard.

The standard Cox hazard model rests on the assumption of time-invariant covariates. In other words, variables should remain constant through the observed period. In the context of firm survival, only some variables can meet the requirement, for instance, a firm's ownership status and organization type. Variables like employment number and agglomeration level, however, change value over time. These variables are known as Type I time-varying covariates (time-dependent variables). Having both time-invariant and Type I time-varying covariates in the model, the essay adopted an extended Cox model as follows:

$$h(t) = h_0(t)\exp\{\beta_1 x + \beta_2 y(t)\} \quad (3)$$

where $y(t)$ denotes covariates with values vary by year.

There is a second type of time-varying covariates (Type II time-varying covariates, also known as time-varying coefficients) which violates the proportional hazard assumption of the standard Cox model. Cox model assumes the hazard ratio of variables is the same throughout the study period. For example, if the hazard for firms locating in employment centers is twice the rate as that for those located in the periphery (HR = 2.0), the proportional hazard assumption implies firms locating in employment centers face the twice hazard rate at 1 year, at 2 years, or at any year until their death. But in reality, hazard could decrease or increase over time. The hazard ratio of firm size is one typical example. The initial firm size is critical in determining firm survival in the first few years. However, the benefit from a large firm size decreases as the firm matures over time. In the presence of Type II time-varying covariates, interaction terms between time and Type II time-varying covariates should be added to the extended Cox model. This changes the model to:

$$h(t) = h_0(t)\exp\{\beta_1 x + \beta_2 y(t) + g(t)[\beta_3 z + \beta_4 w(t)]\} \tag{4}$$

where $g(t)$ is a function of time and, z represent a set of Type II time-varying covariates with invariant value and $w(t)$ is a set of variables that are both Type I time-varying covariates and Type II time-varying covariates.

One can also address Type II time-varying covariates with a parametric regression, for instance, the Accelerated Failure Time model (AFT). Unlike Cox model reporting the impact of the change of regressor on hazard, the AFT model reports the impact of the change of regressor on survival time. A basic AFT model is specified as:

$$\ln t = x'\beta + \varepsilon \tag{5}$$

where ε denotes the error term which can comply with different distributions. This suggests, in use of a parametric model, a better fitted duration distribution should be decided. In the AFT model, the hazard is expressed as:

$$h(t|x) = h_0(t \exp(-x'\beta)) \exp(x'\beta) \tag{6}$$

The specification of the hazard function indicates the hazard in not proportional anymore, and the baseline hazard can be accelerated if $\exp(-x'\beta) > 1$ or decelerated if $\exp(-x'\beta) < 1$.

In this essay, I will first use an extended Cox model considering only time-invariant and Type I time-varying covariates. If any violation of the proportional hazard assumption is identified, an extended Cox model considering Type II time-varying covariates and an AFT model will be applied to do follow-up checks.

3.3.3 Data

The analysis in this essay uses several data sources, with a major reliance on the National Establishment Time-Serials (NETS) database. The NETS database is originally created by Dun and Bradstreet (D&B) for business credit purpose, but recently converted to statistical use. It tracks millions of firms in the United States since their creation, and reports employment, sales, location, corporate status and other related information based on annual snapshots (taken every January).[21] The

[21] Refer Neumark et al., (2005) for a detailed description of NETS.

essay targets new entrants of five industries born in Maryland between January 1992 and January 1993, and tracks their survival until January 2006.[22] The 1992 cohort is selected since it was the first year D&B used yellow pages to identify business units which greatly improves NETS data quality (Neumark et al., 2005). The five industries under study are Construction (NAICS 23), Information (NAICS 51), Finance and Insurance (NAICS 52), Professional, Scientific, and Technical Services (NAICS 54), Administrative and Support and Waste Management and Remediation Services (NAICS 56). These industries are important enough to have been frequently selected to conduct focal analysis in previous studies (Niu et al., 2015). Particularly, all five industries are pillars of the local economy as they generate about 30 percent of jobs and 40 percent of firms in Maryland. In addition, these industries create substantial numbers of new firms: 36 percent of all new entrants in Maryland in 1992, which helps form a representative sample for survival study.

A series of firm-specific and location-specific control variables are included as shown in Table 3.2. The size of a firm is considered as an indicator for the realization of internal scale economy, the access to financial capital and the sunk cost in non-transferable assets that dissuade exit (Caves and Porter, 1975). Dummy variables of a firm's organization and ownership are included to measure different survival opportunities by firm type. The population within 30 miles to a firm is

[22] 2006 is chosen as the cut off time to exclude the influence from the later financial crisis.

aggregated to serve as a proxy for local demand.[23] Accessibility, wage and rent levels are accounted for in measuring firm operation cost and factor cost. Accessibility is captured by the number of metro rail stations within one-mile walking distance to a firm, and by the actual distance from the business location to the nearest highway.[24] Industry wage data is directly taken from County Business Pattern and Quarterly Census of Employment and Wages datasets. Limited by data availability, the average wage at the county level is applied.[25] The rent level is assessed by the average unit commercial property value within proximity to firms' location, with data obtained from Maryland Property View Data Year 2000.[26] Both wage and property values are in 2000 US dollars. In the Cox model, a positive coefficient of a variable indicates a negative impact of that variable on firm survival; conversely, a negative coefficient suggests a positive impact. Finally, county fixed

[23] Data is drawn upon U.S. 2000 decennial census. The unit applied is census tract. If a census tract intersects with a 30-mile buffer line, the taken in population of that census tract is calculated by the total population of that census tract times the ratio of its land area falls within the 30-mile buffer.

[24] The metro rail stations include all WMATA stations, Baltimore Metro Subway stations, Baltimore Light Rail stations and MARC Train stations.

[25] Due to disclosure restrictions, both CBP and QCEW have a mild data missing issue. However, by using CBP and QCEW comparably, the essay is able to construct an estimated wage data set.

[26] Since MD Property View database only contains properties that had been sold or are currently for sale, the exact commercial property unit/units a firm resides in may not be included in the database. After dropping out missing values and outliners, the essay uses 22817 commercial properties to generate the variable. For majority establishments, the proximity to commercial properties is defined within one-mile distance to establishment location, for those don't have commercial property record within one-mile buffer, a two miles buffer is applied instead. For the 180 establishments that do not have any commercial properties within a two-mile buffer, the property value of the nearest commercial property is taken.

effect is controlled in all models to gauge the influences of other county-specific demographic feature, economic policy and natural endowment.

Table 3.2 Descriptive Statistics for Survival Analysis

	Construction (NAICS 23)	**Information** (NAICS 51)	**Finance and Insurance** (NAICS 52)	**Professional, Scientific, and Technical Services** (NAICS 54)	**Administrative and Support and Waste Management and Remediation Services** (NAICS 56)
Employment center	0.120	0.271	0.377	0.358	0.204
	(0.325)	(0.445)	(0.485)	(0.480)	(0.403)
Location quotient: 0-1 mile	2.455	1.124	1.238	1.037	1.306
	(2.451)	(1.373)	(1.202)	(0.733)	(1.601)
Location quotient: 0-5 mile	1.594	0.980	1.049	0.974	1.170
	(0.985)	(0.490)	(0.565)	(0.463)	(0.647)
Diversity: 0-1 mile	0.192	0.156	0.146	0.157	0.171
	(0.127)	(0.086)	(0.067)	(0.088)	(0.101)
Diversity: 0-5 mile	0.106	0.099	0.101	0.099	0.103
	(0.047)	(0.023)	(0.033)	(0.030)	(0.039)
Total employment (Log): 0-1 mile	7.358	8.538	8.937	8.787	8.057
	(2.037)	(1.695)	(1.607)	(1.946)	(1.856)
Total employment (Log): 0-5 mile	10.661	11.416	11.371	11.490	11.069
	(1.628)	(1.373)	(1.301)	(1.362)	(1.459)
Size (Log)	1.018	1.486	1.509	1.004	1.134
	(0.901)	(1.462)	(1.076)	(0.975)	(1.045)
Age(Log)	1.412	1.428	1.505	1.419	1.409
	(0.813)	(0.819)	(0.813)	(0.810)	(0.811)
Headquarter/Branch	0.071	0.306	0.488	0.113	0.131
	(0.256)	(0.461)	(0.500)	(0.317)	(0.337)
Subsidiary	0.007	0.011	0.036	0.005	0.006
	(0.081)	(0.103)	(0.187)	(0.073)	(0.075)
Sole proprietorship	0.275	0.252	0.129	0.291	0.262
	(0.447)	(0.434)	(0.335)	(0.454)	(0.440)
Minority	0.036	0.034	0.020	0.052	0.057
	(0.187)	(0.182)	(0.140)	(0.223)	(0.232)
Women	0.048	0.104	0.045	0.135	0.164
	(0.215)	(0.305)	(0.207)	(0.342)	(0.370)
Foreign	0.003	0.024	0.020	0.005	0.010
	(0.058)	(0.152)	(0.138)	(0.074)	(0.100)
Public	0.007	0.128	0.278	0.019	0.024
	(0.085)	(0.334)	(0.448)	(0.136)	(0.152)
Population (Log)	14.979	15.191	15.025	15.186	15.095
	(0.782)	(0.644)	(0.783)	(0.625)	(0.742)
Station (Log)	0.142	0.319	0.375	0.444	0.222
	(0.376)	(0.592)	(0.699)	(0.769)	(0.502)
Highway (Log)	0.364	0.067	-0.268	-0.163	0.166
	(1.380)	(1.269)	(1.520)	(1.576)	(1.336)
Wage (Log)	10.467	10.773	10.722	10.816	9.994
	(0.165)	(0.214)	(0.282)	(0.200)	(0.163)
Property value (Log)	4.692	4.882	5.011	5.075	4.762
	(0.748)	(0.787)	(0.970)	(1.043)	(0.735)

standard errors are in parentheses.

3.4 Results

3.4.1 Basic estimation

Type I time-varying and time-invariant covariates are considered in the basic estimation. Column 1 of Table 3.3 and Table 3.4 present the hazard estimates of agglomeration indicators at one-mile and five-mile buffer as well as the control variables. The agglomeration of own industry and of other industries impact on firm survival opportunity differently. The estimated coefficient of LQ is not significant for all five industries at either one-mile buffer or five-mile buffer. It suggests Marshall externalities stem from the concentration of employment in the same industry equalize the diseconomy brought by the concentration of rival firms. Diversity influences the survival of firms in two industries at the one-mile buffer. A 0.1 increase in diversity leads to 6.26% and 10.54% increase in hazard for Professional, Scientific, and Technical Services firms and Administrative and Support and Waste Management and Remediation firms respectively. However, the interpretation of diversity's negative impact should be cautious since the estimates may result from firm sorting. New firms prefer diversified locations to test their novel ideas (Duranton and Puga, 2001). Successful innovations are rare, a lot of firms fail to find an ideal prototype and quit the market. The concentration of those "vulnerable" new firms in more diversified locations overestimates the negative effect of diversity on firm survival.

Table 3.3 Cox Hazard Estimation with Type I Time-Varying Covariates: 0-1 Mile

	Construction (NAICS 23)		Information (NAICS 51)		Finance and Insurance (NAICS 52)	
	(1)	(2)	(1)	(2)	(1)	(2)
Employment center		-0.087		0.027		-0.145
		(0.080)		(0.140)		(0.101)
Location quotient: 0-1 mile	0.001	0.002	0.002	0.002	-0.028	-0.030
	(0.013)	(0.013)	(0.032)	(0.032)	(0.036)	(0.036)
Diversity: 0-1 mile	0.379	0.369	-0.045	-0.050	-0.816	-0.763
	(0.202)	(0.202)	(0.517)	(0.519)	(0.500)	(0.501)
Total employment (Log): 0-1 mile	0.065**	0.072**	0.136**	0.132**	0.083*	0.109**
	(0.020)	(0.021)	(0.046)	(0.051)	(0.034)	(0.039)
Size (Log)	-0.282**	-0.281**	-0.133	-0.133	-0.162**	-0.158**
	(0.043)	(0.043)	(0.069)	(0.069)	(0.052)	(0.052)
Headquarter/Branch	-0.280*	-0.270*	-0.427*	-0.428*	-0.794**	-0.799**
	(0.114)	(0.115)	(0.178)	(0.178)	(0.113)	(0.113)
Subsidiary	-0.331	-0.334	0.245	0.248	-0.654*	-0.669*
	(0.197)	(0.199)	(0.332)	(0.329)	(0.269)	(0.270)
Sole proprietorship	-0.806**	-0.804**	-0.582**	-0.582**	-0.555**	-0.559**
	(0.074)	(0.074)	(0.146)	(0.146)	(0.125)	(0.125)
Minority	-1.420**	-1.424**	-0.518	-0.516	-1.149**	-1.140**
	(0.256)	(0.255)	(0.325)	(0.325)	(0.401)	(0.400)
Women	-1.052**	-1.050**	-1.236**	-1.237**	-1.183**	-1.196**
	(0.176)	(0.175)	(0.248)	(0.248)	(0.270)	(0.268)
Foreign	-0.649	-0.646	-1.194	-1.192	0.559	0.549
	(0.504)	(0.494)	(0.679)	(0.679)	(0.301)	(0.301)
Public	-0.117	-0.102	-0.257	-0.260	0.340**	0.342**
	(0.292)	(0.292)	(0.223)	(0.223)	(0.127)	(0.127)
Population (Log)	2.402	2.379	8.732	8.721	2.804	2.776
	(1.698)	(1.698)	(4.612)	(4.609)	(3.320)	(3.316)
Station (Log)	-0.011	0.006	-0.097	-0.099	-0.078	-0.055
	(0.064)	(0.065)	(0.107)	(0.108)	(0.088)	(0.090)
Highway (Log)	-0.017	-0.016	0.002	0.002	-0.004	-0.002
	(0.022)	(0.022)	(0.050)	(0.050)	(0.032)	(0.033)
Wage (Log)	-2.004*	-2.016*	0.760	0.761	0.574	0.578
	(0.960)	(0.960)	(0.898)	(0.898)	(0.781)	(0.780)
Property value (Log)	0.014	0.018	0.037	0.037	-0.089	-0.088
	(0.033)	(0.033)	(0.066)	(0.066)	(0.062)	(0.062)
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of subjects	2838	2838	657	657	1340	1340
No. of failures	1925	1925	435	435	794	794
Time at risk	19257	19257	4503	4503	10395	10395
Wald χ^2	355.86	358.35	742.93	742.40	183.47	188.39
Log pseudolikelihood	-14132.60	-14132.03	-2529.25	-2529.23	-5278.22	-5277.24

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.

Table 3.3 Cox Hazard Estimation with Type I Time-Varying Covariates: 0-1 Mile (continue)

	Professional, Scientific, and Technical Services (NAICS 54)		Administrative and Support and Waste Management and Remediation Services (NAICS 56)	
	(1)	(2)	(1)	(2)
Employment center		-0.078		-0.041
		(0.053)		(0.093)
Location quotient: 0-1 mile	0.008	0.014	-0.024	-0.024
	(0.026)	(0.026)	(0.023)	(0.023)
Diversity: 0-1 mile	0.486*	0.515*	0.720*	0.724*
	(0.215)	(0.216)	(0.331)	(0.331)
Total employment (Log): 0-1 mile	0.045**	0.057**	0.077**	0.082**
	(0.014)	(0.016)	(0.024)	(0.026)
Size (Log)	-0.193**	-0.191**	-0.165**	-0.165**
	(0.028)	(0.028)	(0.047)	(0.047)
Headquarter/Branch	-0.265**	-0.261**	-0.520**	-0.515**
	(0.071)	(0.071)	(0.119)	(0.119)
Subsidiary	-0.677*	-0.680*	-0.271	-0.265
	(0.302)	(0.299)	(0.384)	(0.383)
Sole proprietorship	-0.609**	-0.610**	-0.634**	-0.636**
	(0.051)	(0.051)	(0.093)	(0.094)
Minority	-1.078**	-1.081**	-0.970**	-0.972**
	(0.131)	(0.132)	(0.209)	(0.209)
Women	-1.077**	-1.079**	-0.904**	-0.903**
	(0.071)	(0.071)	(0.101)	(0.101)
Foreign	0.257	0.260	-0.089	-0.078
	(0.211)	(0.210)	(0.335)	(0.337)
Public	-0.073	-0.071	0.090	0.096
	(0.166)	(0.165)	(0.222)	(0.223)
Population (Log)	1.813	1.782	5.202*	5.179*
	(1.606)	(1.605)	(2.542)	(2.543)
Station (Log)	-0.095*	-0.084*	-0.022	-0.013
	(0.039)	(0.041)	(0.072)	(0.075)
Highway (Log)	-0.012	-0.009	0.010	0.011
	(0.015)	(0.015)	(0.029)	(0.029)
Wage (Log)	-0.275	-0.278	0.447	0.447
	(0.334)	(0.335)	(0.596)	(0.596)
Property value (Log)	-0.045	-0.046*	0.020	0.021
	(0.023)	(0.023)	(0.045)	(0.045)
County Fixed Effect	Yes	Yes	Yes	Yes
No. of subjects	5286	5286	1819	1819
No. of failures	3538	3538	1192	1192
Time at risk	36834	36834	12417	12417
Wald χ^2	700.86	702.66	281.96	282.38
Log pseudolikelihood	-28179.81	-28178.75	-8179.29	-8179.19

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.

Table 3.4 Cox Hazard Estimation with Type I Time-Varying Covariates: 0-5 Mile

	Construction (NAICS 23)		Information (NAICS 51)		Finance and Insurance (NAICS 52)	
	(1)	(2)	(1)	(2)	(1)	(2)
Employment center		-0.011		0.162		-0.060
		(0.076)		(0.124)		(0.093)
Location quotient: 0-5 mile	0.009	0.009	0.096	0.081	-0.034	-0.024
	(0.041)	(0.041)	(0.132)	(0.135)	(0.102)	(0.102)
Diversity: 0-5 mile	-0.028	-0.027	-2.677	-2.724	-0.938	-0.933
	(0.719)	(0.719)	(2.829)	(2.837)	(1.593)	(1.591)
Total employment (Log): 0-5 mile	0.093*	0.094*	0.191**	0.186**	0.094	0.101
	(0.037)	(0.037)	(0.070)	(0.070)	(0.054)	(0.056)
Size (Log)	-0.274**	-0.273**	-0.131	-0.132	-0.154**	-0.152**
	(0.043)	(0.043)	(0.067)	(0.067)	(0.052)	(0.052)
Headquarter/Branch	-0.271*	-0.269*	-0.363*	-0.377*	-0.781**	-0.781**
	(0.114)	(0.115)	(0.175)	(0.175)	(0.112)	(0.112)
Subsidiary	-0.326	-0.326	0.169	0.196	-0.619*	-0.620*
	(0.200)	(0.200)	(0.314)	(0.310)	(0.266)	(0.267)
Sole proprietorship	-0.808**	-0.808**	-0.591**	-0.584**	-0.551**	-0.554**
	(0.074)	(0.074)	(0.143)	(0.143)	(0.126)	(0.125)
Minority	-1.442**	-1.443**	-0.509	-0.503	-1.089**	-1.085**
	(0.255)	(0.255)	(0.310)	(0.310)	(0.401)	(0.402)
Women	-1.059**	-1.059**	-1.217**	-1.222**	-1.206**	-1.211**
	(0.173)	(0.173)	(0.244)	(0.245)	(0.271)	(0.270)
Foreign	-0.614	-0.613	-1.254	-1.233	0.560	0.558
	(0.490)	(0.489)	(0.695)	(0.696)	(0.301)	(0.301)
Public	-0.115	-0.113	-0.260	-0.281	0.335**	0.335**
	(0.296)	(0.296)	(0.224)	(0.224)	(0.126)	(0.126)
Population (Log)	2.439	2.435	8.879	8.846	2.948	2.937
	(1.697)	(1.697)	(4.643)	(4.634)	(3.356)	(3.355)
Station (Log)	0.029	0.032	0.014	-0.028	-0.042	-0.024
	(0.063)	(0.065)	(0.098)	(0.103)	(0.082)	(0.087)
Highway (Log)	-0.021	-0.021	0.006	0.011	-0.013	-0.014
	(0.022)	(0.022)	(0.051)	(0.051)	(0.032)	(0.032)
Wage (Log)	-2.036*	-2.038*	0.693	0.706	0.566	0.570
	(0.962)	(0.962)	(0.895)	(0.896)	(0.783)	(0.783)
Property value (Log)	0.022	0.023	0.050	0.044	-0.079	-0.078
	(0.033)	(0.033)	(0.065)	(0.065)	(0.062)	(0.062)
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of subjects	2838	2838	657	657	1340	1340
No. of failures	1925	1925	435	435	794	794
Time at risk	19250	19250	4503	4503	10395	10395
Wald χ^2	347.47	347.87	727.57	728.86	178.02	179.81
Log pseudolikelihood	-14136.24	-14136.23	-2529.51	-2528.71	-5280.48	-5280.29

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.

Table 3.4 COX Hazard Estimation with Type I Time-Varying Covariates: 0-5 Mile (continue)

	Professional, Scientific, and Technical Services (NAICS 54)		Administrative and Support and Waste Management and Remediation Services (NAICS 56)	
	(1)	(2)	(1)	(2)
Employment center		-0.005		0.053
		(0.047)		(0.086)
Location quotient: 0-5 mile	-0.086	-0.085	-0.086	-0.086
	(0.057)	(0.057)	(0.055)	(0.055)
Diversity: 0-5 mile	0.599	0.603	-2.130	-2.146
	(0.934)	(0.935)	(1.206)	(1.206)
Total employment (Log): 0-5 mile	0.118**	0.119**	0.134**	0.131**
	(0.025)	(0.025)	(0.039)	(0.039)
Size (Log)	-0.189**	-0.188**	-0.151**	-0.152**
	(0.028)	(0.028)	(0.047)	(0.047)
Headquarter/Branch	-0.268**	-0.268**	-0.496**	-0.503**
	(0.071)	(0.071)	(0.120)	(0.121)
Subsidiary	-0.648*	-0.648*	-0.263	-0.269
	(0.297)	(0.296)	(0.384)	(0.384)
Sole proprietorship	-0.617**	-0.617**	-0.625**	-0.622**
	(0.051)	(0.051)	(0.094)	(0.094)
Minority	-1.085**	-1.085**	-1.005**	-1.001**
	(0.132)	(0.132)	(0.207)	(0.207)
Women	-1.084**	-1.084**	-0.904**	-0.905**
	(0.071)	(0.071)	(0.101)	(0.101)
Foreign	0.263	0.264	-0.074	-0.092
	(0.212)	(0.212)	(0.336)	(0.340)
Public	-0.064	-0.063	0.126	0.113
	(0.166)	(0.166)	(0.220)	(0.221)
Population (Log)	1.947	1.945	5.641*	5.681*
	(1.606)	(1.606)	(2.569)	(2.567)
Station (Log)	-0.064	-0.063	0.033	0.017
	(0.037)	(0.040)	(0.068)	(0.074)
Highway (Log)	-0.006	-0.006	0.014	0.013
	(0.015)	(0.015)	(0.029)	(0.029)
Wage (Log)	-0.286	-0.286	0.471	0.472
	(0.333)	(0.333)	(0.597)	(0.597)
Property value (Log)	-0.031	-0.031	0.033	0.032
	(0.023)	(0.023)	(0.045)	(0.045)
County Fixed Effect	Yes	Yes	Yes	Yes
No. of subjects	5286	5286	1819	1819
No. of failures	3538	3538	1192	1192
Time at risk	36834	36834	12417	12417
Wald χ^2	701.73	701.99	292.86	292.86
Log pseudolikelihood	-28176.76	-28176.75	-8178.07	-8177.88

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.

Urbanization agglomeration is revealed with a prominent negative effect. As reported in Table 3.3 and Table 3.4, the coefficient of total employment is consistently negative and significant in all models except for Finance and Insurance industry at the five-mile buffer. Double the total employment within one-mile buffer of firms is forecasted to increase the hazard by 6.74% for Construction firms, 14.58% for Information firms, 8.63% for Finance and Insurance firms, 4.56% for Professional, Scientific, and Technical Services firms, and 7.98% for Administrative and Support and Waste Management and Remediation Services firms. Similarly, a doubling of the total employment within five-mile buffer of firms would increase the hazard by 9.78% for Construction firms, 21% for Information firms, 9.88% for Finance and Insurance firms, 12.55% for Professional, Scientific, and Technical Services firms, and 14.36% for Administrative and Support and Waste Management and Remediation Services firms.

Together the negative estimates of diversity and total employment indicate a strong selection effect forced by cross-industry concentration. Given the survival chance of a firm is positively correlated with its productivity, the lower survival rate would suggest a higher productivity of marginal surviving firms in denser areas. This is in line with the argument made in Asplund and Nocke (2006), Melitz and Ottaviano (2008) and Comes et al. (2012), that bigger cities achieve high productivity level partially by eliminating less-productive firms through firm selection.

Column 2 of Table 3.3 and Table 3.4 show the results with adding employment centers indicator in the model. Employment centers is a determinant factor for firm birth (Niu et al., 2015), but it doesn't show much impact on firm survival. It is possible the agglomerative impact of employment centers is captured by specialization, urbanization and diversity indicators. But one can also interpret the result as the negative impact and positive impact of employment centers on survival equalizes each other.

The estimation results of control variables are generally as expected. For most firms except those in the Information industry, a larger firm size is associated with a greater survival opportunity. The longevity of larger firms is likely owing to their stronger internal scale economy and access to different types of capital (Audretsch, 1991; Audrestsch and Mahmood, 1995). Compared to standalone firms, headquarters and branches are predicted to have a longer life expectancy. Subsidiaries in Finance and Insurance industry and Professional, Scientific, and Technical Services industry better survive than non-subsidiaries in those two industries. Firms like headquarters, branches and subsidiaries succeed with a better survival chance since they have the advantage of accessing abundant resources and rich operation experience over standalone and non-subsidiary firms (Dunne et al., 1989). A higher survival rate is also found in sole proprietorships.[27] One possible

[27] Sole proprietorships defined is this dissertation have only one workers, while in sole proprietorships may occasionally hire a few more workers.

reason for their longevity is that the cost for them to stay in the market is relatively low since they do not need to hire workers or rent big offices. Most minority-owned and women-owned firms show a higher survival rate. On one hand, the higher survival rate could be attributed to these firms' delivery of specialized goods and services that meet the needs of ethical groups or women (Robb, 2002). On the other hand, it is true that minorities and women have more difficulties to be hired with their desired or matched jobs in the labor market, leaving them fewer choices but to sustain their own business for a living. Only the survival of Finance and Insurance firms is affected by public ownership. The positive coefficient implies a higher mortality rate for public owned financial and insurance firms. No significant impact is found for foreign ownership on firm survival.

Results of other locational factors are also most consistent with existing discussions in literature. The coefficient of the population variable shows a positive sign as with the previous revelation of firms in the populated area having a lower survival rate (Acs et al., 2007; Yu et al., 2009). But it is only statistically significant for Administrative and Support and Waste Management and Remediation Services industry. Highway accessibility is not predicted with a statistically significant effect on firm survival in Maryland. Accessibility to metro and rail stations influence firm survival in Professional, Scientific, and Technical Services industry when agglomeration is measured at the one-mile buffer. Doubling metro and rail station number within one-mile distance to Professional, Scientific, and Technical Services firms decreases those firms' hazard rate by 9.07%.

Wage and property value do not present significant impacts on most industries: wage affects only the survival of Construction firms while property value matters only the survival of Professional, Scientific, and Technical Services firms. High wages of construction firms may indicate high productivity of workers as well as a hot local housing market, both of which are beneficial for the survival of construction firms. Similarly, property value proxies rent level but also suggest local amenities. The Professional, Scientific, and Technical Services firms are more likely to value and take advantage of better local amenities thus their survival positively links to property value.

3.4.2 Discussion

3.4.2.1 Cox Model with Time Interaction Term

The above analysis treats the hazard ratio constant over time. To examine the potential violation of proportional hazard assumption in the basic estimation, this essay runs a test for proportional hazard by checking a nonzero slope in a generalized linear regression of the scaled Schoenfeld residuals on time. The result suggests for each of the studied industries, there are variables that violate the proportional hazard assumption, indicating impacts of these covariates vary as firm aging. To address this issue, the essay includes interaction terms of those variables and a function of time $f(t)$.[28] Column 1 of Table 3.5 and Table 3.6 present the estimates when time function is specified as $f(t) = t$. Alternative time functions are applied and the results are similar.[29]

The inclusion of time interaction term does not significantly impact the coefficients and significance of agglomeration indicators. Urbanization presents similar negative impact on survival as in the basic estimation. Specialization shows zero significant externalities in all cases. Similar estimates of diversity coefficients also hold except for Finance and Insurance industry. For Finance and Insurance firms, diversity at one-mile buffer generates some benefits on their survival as firms aging. In long term, diversity eliminates random shocks across industries and provides a steady demand for financial and insurance services. The coefficient of employment center becomes significant for Professional, Scientific and Technical service firms. Interestingly, it shows employment centers jeopardize firms' survival in their early years, however, the hazard diminishes over time. For Professional, Scientific and Technical service firms survive beyond 3 or 4 years, employment centers even benefit their future survival. This suggests there are some benefits from the higher employment density of employment centers.

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[28] $f(t)$ does not equal $g(t)$ defined in Eq. 4. Assume $h(t) = h_0(t)\exp\left(\beta_1 x_1 + \beta_2 x_1 f(t)\right)$, then $g(t) = \left(1 + \frac{\beta_2}{\beta_1} f(t)\right)$.

[29] The essay also tests with $f(t) = log(t)$ and $f(t) = exp(-0.139 * t)$. The second function specifies that the covariate becomes half value in the interaction term at *t=5*. Results using other time functions are available upon request.

Table 3.5 Cox Hazard and AFT Estimation with Type I and Type II Time-Varying Covariates: 0-1 Mile

	Construction (NAICS 23)		Information (NAICS 51)		Finance and Insurance (NAICS 52)		Professional, Scientific, and Technical Services (NAICS 54)		Administrative and Support and Waste Management and Remediation Services (NAICS 56)	
	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)
Employment center	-0.087	0.031	0.048	-0.032	-0.146	0.049	0.222*	0.022	-0.037	0.014
	(0.077)	(0.031)	(0.137)	(0.058)	(0.100)	(0.041)	(0.087)	(0.017)	(0.091)	(0.034)
Location quotient: 0-1 mile	0.003	-0.002	0.006	-0.007	-0.028	0.015	0.013	-0.005	-0.025	0.006
	(0.013)	(0.005)	(0.030)	(0.012)	(0.035)	(0.014)	(0.026)	(0.008)	(0.023)	(0.008)
Diversity: 0-1 mile	0.357	-0.145	-0.026	-0.031	0.928	0.261	0.470*	-0.206**	0.753*	-0.272*
	(0.199)	(0.075)	(0.502)	(0.230)	(0.925)	(0.205)	(0.212)	(0.067)	(0.326)	(0.118)
Total employment (Log): 0-1 mile	0.073**	-0.027**	0.127*	-0.043*	0.115**	-0.037*	0.057**	-0.017**	0.080**	-0.025**
	(0.020)	(0.008)	(0.051)	(0.021)	(0.038)	(0.016)	(0.016)	(0.005)	(0.026)	(0.009)
Employment center×Year							-0.061**			
							(0.015)			
Diversity×Year: 0-1 mile					-0.368**					
					(0.138)					
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of subjects	2838	2838	657	657	1340	1340	5286	5286	1819	1819
No. of failures	1925	1925	435	435	794	794	3538	3538	1192	1192
Time at risk	19257	19257	4503	4503	10395	10395	36834	36834	12417	12417
Wald χ^2	492.28	2402.01	859.97	1.26E+07	217.5	1073.75	915.77	6053.37	361.92	1816.05
Log pseudolikelihood	-14077.279	-3167.0806	-2509.14	-717.31469	-5259.86	-1492.118	-28029	-5524.0867	-8137.55	-1908.2207

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.All other variables listed in Table 3 along with their interaction terms with a function of time are included in the model: coefficients for those variables are not reported to conserve space.

Table 3.6 Cox Hazard and AFT Estimation with Type I and Type II Time-Varying Covariates: 0-5 Mile

	Construction (NAICS 23)		**Information** (NAICS 51)		**Finance and Insurance** (NAICS 52)		**Professional, Scientific, and Technical Services** (NAICS 54)		**Administrative and Support and Waste Management and Remediation Services** (NAICS 56)	
	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)
Employment center	-0.011	0.003	0.183	-0.075	-0.054	0.016	0.301**	-0.002	0.054	-0.015
	(0.074)	(0.030)	(0.119)	(0.053)	(0.091)	(0.038)	(0.083)	(0.015)	(0.084)	(0.032)
Location quotient: 0-5 mile	0.008	-0.013	0.081	-0.070	-0.018	0.019	-0.086	0.022	-0.082	0.024
	(0.041)	(0.015)	(0.133)	(0.051)	(0.103)	(0.042)	(0.056)	(0.017)	(0.054)	(0.020)
Diversity: 0-5 mile	-0.118	0.215	-2.712	2.006	-1.040	0.342	0.503	-0.143	-1.964	0.785
	(0.719)	(0.263)	(2.807)	(1.179)	(1.560)	(0.665)	(0.926)	(0.288)	(1.191)	(0.445)
Total employment (Log): 0-5 mile	0.091*	-0.041**	0.187**	-0.060*	0.104	-0.029	0.116**	-0.031**	0.130**	-0.042**
	(0.036)	(0.014)	(0.069)	(0.028)	(0.055)	(0.022)	(0.025)	(0.008)	(0.038)	(0.014)
Employment center×Year							-0.062**			
							(0.015)			
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of subjects	2838	2838	657	657	1340	1340	5286	5286	1819	1819
No. of failures	1925	1925	435	435	794	794	3538	3538	1192	1192
Time at risk	19250	19250	4503	4503	10395	10395	36834	36834	12417	12417
Wald χ^2	474.6	2347.43	879.02	660798.8	199.18	1068.25	916.26	6048.5	369.72	1549.07
Log pseudolikelihood	-14081.6	-3171.036	-2505.18	-715.96964	-5266.08	-1495.0728	-28027.1	-5526.5363	-8136.89	-1907.8688

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.All other variables listed in Table 4 along with their interaction terms with a function of time are included in the model: coefficients for those variables are not reported to conserve space.

3.4.2.2 AFT Estimation

The essay also carries out a robustness check by applying AFT model. The data is fit into different models and the regression results of the Weibull model is presented since it is the best-fitting model based on Akaike's information criterion and Bayesian information criterion.[30] In AFT model, a negative/increase coefficient suggests an increase/decrease in hazard. Column 2 of Table 3.5 and Table 3.6 presents similar findings as in the extended Cox model with time interaction terms. Urbanization agglomeration at one-mile buffer extends firm survival for all five industries and urbanization agglomeration at five-mile buffer benefits firm survival for four industries except Finance and Insurance. Diversity increases hazard for firms in Professional, Scientific, and Technical Services industry and Administrative and Support and Waste Management and Remediation industry at the one-mile buffer. The coefficients of specialization and employment centers are statistically insignificant for all industries.

3.4.2.3 Selection bias

The negative impact of urbanization agglomeration and diversity on firm survival could be overestimated if weak firms disproportionally locate in dense areas. To examine whether the concentration of weak firms distorts the results, the essay separately runs regression on mature firms as suggested by De Silva and McComb

[30] The models have been considered include Weibull model, exponential model, lognormal model, loglogistic model, generalized gamma model.

(2012). De Silva and McComb (2012) define mature firms as those surviving three years and longer. This essay extends the survival year to at least five years in defining mature firms to further eliminate the disturbance of weak firms. For the studied five industries, about 46.73% to 56.72% of firms survived after five years.

The estimates in Table 3.7 and Table 3.8 show some change of the agglomeration effect on firm survival especially for diversity, specialization and employment centers. Diversity no longer jeopardizes the survival of mature firms in Professional, Scientific, and Technical Services industry, and Administrative and Support and Waste Management and Remediation Services industry. Rather, it sustains the survival of Finance and Insurance firms at the one-mile buffer. It is also interesting to find that employment centers and specialization support the survival of mature firms in some industries. Employment centers provide some benefit on the survival of mature Finance and Insurance firms and Professional, Scientific, and Technical Services firms. This helps explain the concentration of Finance and Insurance, Professional, Scientific, and Technical Services industries in CBD and suburban centers. It also shows specialization benefits the survival of Construction and Finance and Insurance firms although for the latter the benefit only lasts for a short period based on the coefficient value of the extended cox hazard model.

The negative impact of agglomeration consistently comes from urbanization agglomeration. In extended Cox model, urbanization increases hazard for Information firms, Professional, Scientific, and Technical Services firms, and

Administrative and Support and Waste Management and Remediation Services firms. In AFT model, it accelerates the elimination of Construction firms, Information firms and Professional, Scientific, and Technical Services firms at the one-mile buffer; and Information firms, Professional, Scientific, and Technical Services firms, and Administrative and Support and Waste Management and Remediation Services firms when measured at the five-mile buffer. Through the study of mature firms, it is safe to say diseconomies from the overall scale of concentration always overwhelm associated benefits.

Table 3.7 Cox Hazard and AFT Estimation with Type I and Type II Time-Varying Covariates for Mature Firms: 0-1 Mile

	Construction		**Information**		**Finance and Insurance**		**Professional, Scientific, and Technical Services**		**Administrative and Support and Waste Management and Remediation Services**	
	(NAICS 23)		(NAICS 51)		(NAICS 52)		(NAICS 54)		(NAICS 56)	
	Cox with Time Interaction	Weibull AFT	Cox with Time Interaction	Weibull AFT	Cox with Time Interaction	Weibull AFT	Cox with Time Interaction	Weibull AFT	Cox with Time Interaction	Weibull AFT
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Employment center	-0.172	0.043	-0.282	0.082	0.266	0.037	-0.235**	0.066**	-0.078	0.021
	(0.146)	(0.041)	(0.246)	(0.077)	(0.223)	(0.057)	(0.087)	(0.025)	(0.160)	(0.058)
Location quotient: 0-1 mile	0.011	-0.002	-0.047	0.003	-0.189*	-0.009	-0.061	0.005	-0.056	0.018
	(0.020)	(0.005)	(0.087)	(0.027)	(0.092)	(0.017)	(0.048)	(0.013)	(0.041)	(0.014)
Diversity: 0-1 mile	-0.061	-0.015	-0.946	0.372	-1.952*	0.655*	0.071	-0.040	0.576	-0.259
	(0.340)	(0.094)	(1.360)	(0.507)	(0.794)	(0.303)	(0.368)	(0.105)	(0.567)	(0.202)
Total employment (Log): 0-1 mile	0.065	-0.018*	0.221**	-0.057*	0.113	-0.035	0.061*	-0.015*	0.163**	-0.025
	(0.033)	(0.009)	(0.090)	(0.029)	(0.063)	(0.023)	(0.026)	(0.007)	(0.060)	(0.016)
Employment center×Year					-0.124*					
					(0.050)					
Location quotient×Year: 0-1 mile					0.064**					
					(0.018)					
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of subjects	1392	1392	307	307	760	760	2630	2630	880	880
No. of failures	669	669	140	140	308	308	1237	1237	410	410
Time at risk	8007	8007	1918	1918	4889	4889	15380	15380	5115	5115
Wald χ^2	108.77	2633.3	11329.2	493.6	2800.63	1415.17	155.61	3317.68	9127.47	1762.49
Log pseudolikelihood	-4593.6824	-1375.8	-734.79657	-286.607	-1924.3963	-737.059	-9283.7594	-2662.04	-2616.509	-899.748

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.All other variables listed in Table 4 along with their interaction terms with a function of time are included in the model: coefficients for those variables are not reported

Table 3.8 Cox Hazard and AFT Estimation with Type I and Type II Time-Varying Covariates for Mature Firms: 0-5 Mile

	Construction (NAICS 23)		**Information** (NAICS 51)		**Finance and Insurance** (NAICS 52)		**Professional, Scientific, and Technical Services** (NAICS 54)		**Administrative and Support and Waste Management and Remediation Services** (NAICS 56)	
	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)	Cox with Time Interaction (1)	Weibull AFT (2)
Employment center	-0.112	0.024	-0.064	0.035	-0.026	0.002	-0.190*	0.052*	-0.003	0.003
	(0.143)	(0.039)	(0.222)	(0.068)	(0.156)	(0.056)	(0.078)	(0.022)	(0.150)	(0.054)
Location quotient: 0-5 mile	0.129	0.002	-0.011	-0.057	0.041	-0.009	-0.146	0.021	-0.099	0.047
	(0.078)	(0.018)	(0.294)	(0.086)	(0.142)	(0.052)	(0.101)	(0.028)	(0.104)	(0.038)
Diversity: 0-5 mile	-0.020	-0.056	-4.109	1.561	-1.262	-0.081	-0.363	0.093	-2.490	0.590
	(1.183)	(0.295)	(4.987)	(1.414)	(2.101)	(0.737)	(1.396)	(0.371)	(1.456)	(0.405)
Total employment (Log): 0-5 mile	0.064	-0.019	0.315**	-0.075*	-0.003	0.011	0.126**	-0.030**	0.188**	-0.056*
	(0.058)	(0.016)	(0.120)	(0.037)	(0.088)	(0.030)	(0.041)	(0.011)	(0.070)	(0.025)
Location quotient×Year: 0-5 mile	-0.051**									
	(0.019)									
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of subjects	1392	1392	307	307	760	760	2630	2630	880	880
No. of failures	669	669	140	140	308	308	1237	1237	410	410
Time at risk	8002	8002	1918	1918	4889	4889	15380	15380	5115	5115
Wald χ^2	114.82	2617.17	862.6	884.45	3020.85	1426.16	161.1	3238.86	7558.15	1979.05
Log pseudolikelihood	-4591.5846	-1376.08	-732.97693	-286.195	-1933.5143	-740.308	-9282.2937	-2660.85	-2616.1005	-897.876

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.All other variables listed in Table 4 along with their interaction terms with a function of time are included in the model: coefficients for those variables are not reported to conserve

3.4.2.4 Other robustness check

In survival models, firms are censored if they changed industry or location during the observation period. To check if the censoring alters the estimation of agglomerative impact on survival, I run a simple conditional logit estimation by assuming a firm chooses one of the three following options in each observation year: (a). continue operation under current location and industry; (b). exit the market (fail); and (c). switch to another industry or change location or both. Also assumed is a firm's decision in the previous year does not affect its decision in the next year. The estimates in Table 3.9 and Table 3.10 provide a quite robust forecast about the urbanization agglomeration impact. Higher urbanization agglomeration in proximity to a firm makes the firm operation more difficult and leads to a closure of its business. Employment centers reduce the elimination possibility of mature firms in Professional, Scientific, and Technical Services industry. Diversity expedites the death of young Professional, Scientific, and Technical Services firms, and Administrative and Support and Waste Management and Remediation Services firms but deter the bankruptcy of mature Finance and Insurance firms. No significant impact is identified for specialization on firm death. These results are quite similar as those found in the survival estimations.

Table 3.9 Conditional Logit Estimation of Firm Choice: 0-1 mile

	Construction (NAICS 23)		Information (NAICS 51)		Finance and Insurance (NAICS 52)		Professional, Scientific, and Technical Services (NAICS 54)		Administrative and Support and Waste Management and Remediation Services (NAICS 56)	
	All firms (1)	Mature firms (2)	All firms (1)	Mature firms (2)	All firms (1)	Mature firms (2)	All firms (1)	Mature firms (2)	All firms (1)	Mature firms (2)
Death										
Employment center	-0.113	-0.201	0.054	-0.309	-0.158	-0.137	-0.096	-0.258**	-0.035	-0.083
	(0.088)	(0.166)	(0.152)	(0.278)	(0.109)	(0.177)	(0.057)	(0.096)	(0.099)	(0.175)
Location quotient: 0-1 mile	0.005	0.011	0.008	-0.015	-0.039	0.034	0.015	-0.056	-0.029	-0.056
	(0.014)	(0.022)	(0.039)	(0.088)	(0.039)	(0.059)	(0.029)	(0.051)	(0.025)	(0.046)
Diversity: 0-1 mile	0.403	0.065	-0.073	1.340	-0.868	2.196*	0.591*	-0.091	0.828*	-0.705
	(0.246)	(0.390)	(0.623)	(1.366)	(0.557)	(0.959)	(0.242)	(0.387)	(0.371)	(0.618)
Total employment (Log): 0-1 mile	0.083**	0.074*	0.135*	0.232*	0.119**	0.122	0.064**	0.064*	0.087**	0.092
	(0.023)	(0.037)	(0.053)	(0.096)	(0.043)	(0.069)	(0.018)	(0.029)	(0.029)	(0.048)
Relocation/Industry Change										
Employment center	-0.319	-0.960**	0.434	-0.507	0.006	-0.155	-0.100	0.022	0.123	-0.347
	(0.194)	(0.372)	(0.330)	(0.652)	(0.235)	(0.390)	(0.121)	(0.180)	(0.192)	(0.338)
Location quotient: 0-1 mile	-0.102**	-0.168**	-0.052	0.013	-0.042	-0.047	-0.041	0.021	0.002	-0.026
	(0.038)	(0.062)	(0.096)	(0.214)	(0.077)	(0.129)	(0.061)	(0.088)	(0.038)	(0.059)
Diversity: 0-1 mile	0.199	-0.190	-0.527	4.423	0.261	1.325	0.444	-0.277	-0.350	-0.090
	(0.557)	(0.871)	(1.478)	(2.454)	(1.311)	(2.153)	(0.498)	(0.766)	(0.675)	(1.084)
Total employment (Log): 0-1 mile	0.033	0.024	0.035	-0.017	0.068	-0.136	0.033	-0.053	0.051	-0.020
	(0.052)	(0.079)	(0.123)	(0.179)	(0.096)	(0.137)	(0.039)	(0.055)	(0.057)	(0.085)
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	19257	8007	4503	1927	10395	4889	36834	15380	12417	5115
Log likelihood	-7535.8718	-2816.9868	-1745.14	-616.796	-3453.43	-1393.62	-14281.2	-5595.47	-4975.7	-1895.05
LR χ^2	681.92	322.05	210.76	109.09	306.23	177.2	1238.51	375.18	484.3	168.46
Pseudo R^2	0.0433	0.0541	0.0569	0.0812	0.0425	0.0598	0.0416	0.0324	0.0464	0.0426

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.All other variables listed in Table 4 along with their interaction terms with a function of time are included in the model: coefficients for those variables are not reported

Table 3.10 Conditional Logit Estimation of Firm Choice: 0-5 mile

	Construction		**Information**		**Finance and Insurance**		**Professional, Scientific, and Technical Services**		**Administrative and Support and Waste Management and Remediation Services**	
	(NAICS 23)		(NAICS 51)		(NAICS 52)		(NAICS 54)		(NAICS 56)	
	All firms (1)	Mature firms (2)	All firms (1)	Mature firms (2)	All firms (1)	Mature firms (2)	All firms (1)	Mature firms (2)	All firms (1)	Mature firms (2)
Death										
Employment center	-0.029	-0.140	0.187	-0.100	-0.057	-0.030	-0.017	-0.212*	0.061	-0.010
	(0.085)	(0.161)	(0.137)	(0.258)	(0.100)	(0.167)	(0.050)	(0.086)	(0.092)	(0.165)
Location quotient: 0-5 mile	0.020	-0.012	0.125	0.039	-0.100	0.017	-0.077	-0.134	-0.103	-0.121
	(0.047)	(0.073)	(0.152)	(0.313)	(0.116)	(0.159)	(0.065)	(0.111)	(0.062)	(0.113)
Diversity: 0-5 mile	-0.137	0.141	-2.913	5.266	-0.174	0.836	0.766	0.278	-1.892	2.599
	(0.785)	(1.297)	(3.684)	(6.689)	(1.963)	(2.760)	(1.033)	(1.604)	(1.242)	(1.795)
Total employment (Log): 0-5 mile	0.114**	0.081	0.193*	0.326*	0.110	0.001	0.130**	0.137**	0.140**	0.200**
	(0.042)	(0.066)	(0.075)	(0.136)	(0.064)	(0.096)	(0.028)	(0.045)	(0.043)	(0.074)
Relocation/Industry Change										
Employment center	-0.313	-0.919**	0.405	-0.622	0.032	-0.371	-0.100	-0.072	0.171	-0.384
	(0.184)	(0.359)	(0.288)	(0.609)	(0.213)	(0.366)	(0.107)	(0.161)	(0.179)	(0.324)
Location quotient: 0-5 mile	0.033	-0.035	-0.042	0.254	-0.235	-0.130	0.145	0.413*	0.096	-0.102
	(0.121)	(0.200)	(0.366)	(0.681)	(0.233)	(0.305)	(0.134)	(0.211)	(0.109)	(0.195)
Diversity: 0-5 mile	-1.173	0.326	23.002**	7.879	-3.362	0.111	-0.566	-6.522	-1.960	1.022
	(1.784)	(2.614)	(8.374)	(17.764)	(4.840)	(8.004)	(1.939)	(3.715)	(2.263)	(3.609)
Total employment (Log): 0-5 mile	0.258*	0.193	0.253	0.045	0.329*	0.178	0.108	-0.041	0.070	0.017
	(0.104)	(0.161)	(0.195)	(0.253)	(0.159)	(0.231)	(0.059)	(0.085)	(0.087)	(0.128)
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	19250	8007	4503	1927	10395	4889	36834	15380	12417	5115
Log likelihood	-7540.96	-2821.56	-1739.53	-617.851	-3454.31	-1398.13	-14278.2	-5590.74	-4974.56	-1892.39
LR χ^2	670.01	312.91	221.98	106.98	304.47	168.17	1244.45	384.65	486.57	173.77
Pseudo R^2	0.0425	0.0525	0.06	0.0797	0.0422	0.0567	0.0418	0.0333	0.0466	0.0439

** Denotes statistical significance at the 1% level, * denotes statistical significance at the 5% level. Robust standard errors are in parentheses.All other variables listed in Table 4 along with their interaction terms with a function of time are included in the model: coefficients for those variables are not reported to

3.5 Conclusion and Policy Implication

By studying the survival of new firms in Maryland, this essay adds new evidence to the interpretation of agglomerative impact on firm dynamics. It provides some support for the argument that higher mortality rates are the other side of the coin from higher entry rates. The most consistent impact is identified for the overall scale of local agglomeration that it always jeopardizes the survival of individual firms regardless their maturity. Nonetheless, the pressure of survival brought by urbanization agglomeration may help attain economic efficiency. As discussed in firm selection literature, competition for survival pushes firms to be more productive and innovative. Once weak firms exit the market, they release factors of production that nourish the next generation of entrepreneurship (Carlton, 1983). In line with Schumpeter's "creative destruction" theory, the "birth-growth-selection-new birth" process leads to the evolution of the economy. A vivid example is Silicon Valley, where the concentration of high-tech industry causes high firm turnover rate, but great innovations as well (Saxenian, 1996). In contrast, the slow firm turnover in Japan during the 1990s impeded the redistribution of resources and delayed the country's recovery from a stagnated economy (De Veirman and Levin, 2012).

This essay's examination of firm survival also provides a new angle to understand firm birth and new firm location decision-making. Having new firms aware of the greater hazard associated with urbanization before making location decisions, they would have fewer incentives in choosing places categorized with greater urbanization agglomeration. This is in line with previous studies find a less prominent urbanization effect on firm birth (Rosenthal and Strange, 2003; Niu et al., 2015).

With the overall scale of agglomeration being controlled, firms especially mature firms might receive some benefits on survival from a larger share of own industry firms, a more diversified environment and a more intensified concentration. These findings help explain the spatial heterogeneous survival performance of firms in different industries and in economies with different industrial structures.

This essay has important implications for economic development policy and urban planning. First, it should not use firm survival as the single measure of economic performance since lower survival rate might indicate a vibrant economy instead of an economic recession. Governments have paid lots of effort to encourage firm birth and support their long-term business success. However, evidence of this essay along with the case of Silicon Valley and Japan reveals firm survival is not necessarily related to local or national economic success. Policymakers should pay more attention to what causes firm death instead of whether firms die. If firm death is simply due to market competition, no intervention is required. Intervention or correction is only necessary when firms die due to bad policies and inappropriate planning.

Given the potential higher mortality rate associated with concentration, denser areas may not expand as quickly as expected even though they are the hot spots of firm birth. Projection of local growth is not reliable if it is made based on firm birth. The high turnover of firms suggests local governments should think how to fully utilize stock construction land and structure before pursuing any new developments. Failure development has been seen in both developed and developing countries, for instance, the development of shared workspace in China. Co-working is suddenly advocated by local governments and real estate developers in the recent years. Numerous shared offices have been built and transformed in a short period. However, investors overestimated the growth potential of start-ups that rent the co-working offices. Most of start-ups die in their first two years. Thus, although the creation of start-ups is high, they do not generate a constant high demand. It is reported oversupply of co-working spaces appears in several cities of China.[31]

Another policy implication of the second essay is policies should consider firm survival potential by industries. The finding of the essay shows some industries survive better than others in the same place. If certain industries generate additional more agglomeration economies and efficiency in a specific business environment, then economic and planning policies should consider facilitating the concentration of those industries in that specific environment. For instance, as professional and business service firms and financial and insurance firms survive better in employment centers, policies should be adjusted to encourage the concentration of those firms in employment centers.

[31] Refer to http://blog.oddup.com/co-working-spaces-in-hong-kong-are-there-now-too-many/; http://www.yicai.com/news/4719907.html.

Chapter 4: Agglomeration and Intra-Metropolitan Relocation of Service Firms

4.1 Introduction

A firm's original location cannot always be economically optimal given the dynamic nature of firm conditions and the market environment over time. The National Establishment Time Serials (NETS) database reveals that at least 10% of firms experience spatial adjustments of their locations throughout their business's life span. Interregional relocation of headquarters and international relocation of manufacturing plants always draw attention from government entities, scholars and the public. It has been frequently reported in the news that when the headquarters of giant firms, like Bank of America, Boeing, and General Electric announced their intention of relocation, local governments battled for becoming the new host area. The U.S. government is also well acknowledged for its commitment to bringing manufacturing plants, which have been previously relocating to China, Mexico and other third world countries, back to the U.S. territory.

Interregional and international firm relocations, however, are only rare events compared to relocations within metropolitan areas. In fact, long-distance relocation is a challenging task for firms. The sunk investment in non-transferable assets and human capital, the familiarity to local networks and markets, and the unpredictable risks of alternative locations make firms economically daunted by long-distance relocation unless the return on investment of long-distance relocation is overwhelmingly substantial (Pellenbarg, van Wissen and van Dijk, 2002). So far, the primary drivers for large headquarters and manufacturing plants initiating long-distance relocations are the considerable amount of subsidies offered by local government and the tremendous reduction in labor and land costs the new location will yield given their massive volume of production. But short-distance relocation remains more common for most small or medium-sized firms, which prefer and may be able to afford relocation to proximate areas. A study of Dutch firms shows that about 80% of relocated firms and 80% of relocated jobs move to nearby areas, most within the same metropolitan region (VVK, 2003). These kinds of intra-metropolitan relocations save firms from high searching and moving costs, and the risks of losing employees, consumers and local networks.

The same study of VVK (2003) also reveals that in the Netherlands, manufacturing firms only generated about 6% of relocations with 12% of relocated jobs, while service firms accounted for more than 90% of relocations and at least 85% of relocated jobs. A similar pattern is also found in other western European counties and USA. The large share of service firm relocations is not only owing to the service industry as the pillar industry in these countries, but also that service firms naturally are more suitable to be making spatial adjustments. Less capital investment, limited dependence on natural resources, high adaption to teleworking, and less land consumption make service firms more flexible in choosing alternative locations compared to manufacturing plants (Kolko, 2010).

Despite the high volume of intra-metropolitan relocations and service firm relocations, they receive quite limited attention from government and academics. Previous studies detailed how local fiscal differentiation, accessibility level (often measured by distance, travel time, transit accessibility and road network density), cost, demographic features and agglomerative externalities influence firm location and relocation choices at county, Metropolitan Statistical Area (MSA) and country level (Pellenbarg, van Wissen and van Dijk, 2002). However, less evidence is provided upon how these locational factors affect a firm, especially a service firm's intra-metropolitan relocation. It is not clear what and how locational factors cause a service firm to choose an alternative location within the same metropolitan area. Considering intra-metropolitan relocation of service firms could profoundly reshape an urban economic landscape and challenge local planning and policy practices, it is important to dig deeper into the locational factors affecting service firms' intra-metropolitan relocation considerations.

This essay tries to fill the gap in the literature by providing greater details on the relocation choices of service firms within the Baltimore Metropolitan Region.[32] Particularly, it focuses on the role of agglomeration in shaping service firms' intra-metropolitan relocation decisions. Agglomeration externalities have been long recognized to encourage firm birth and relocation at city and metropolitan area levels (Guimarães et al., 2000; Duranton and Puga, 2001; Strauss-Kahn and Vives, 2009; Hong 2014). Recent studies show agglomeration economies attenuate rapidly (Rosenthal and Strange, 2003, 2005), suggesting it could also appositively influence firm location and relocation preference within a city or a metropolitan area. However,

[32] The Baltimore metropolitan area, as defined by the United States Office of Management and Budget, includes Anne Arundel County, Baltimore City, Baltimore County, Carroll County, Harford County, Howard County and Queen Anne's County. Among them, Queen Anne's County is separated from the other counties by the Chesapeake Bay. A lot of studies focusing on the Baltimore metropolitan area exclude Queen Anne's County, so it will be in this essay. The rest of the counties combined form an area commonly known as the Baltimore Metropolitan Region.

the empirical evidence on agglomeration impacts on firm intra-metropolitan relocation is still scant and mixed.

As analysis proceeds, a more detailed review of literature regarding the impact of agglomeration on firm location and relocation choice will be presented in section 2. Section 3 introduces data, variables, and some simple facts about service firms' relocation activities in the Baltimore Metropolitan Region. Section 4 discusses empirical strategies and interprets estimation results. Section 5 concludes the essay with final remarks.

4.2 Literature Review

People and firms agglomerate for many reasons: the access to natural resources, military and political orders, or simply by chance. No matter what the cause or causes are, once spatial concentration is formed, other workers and firms would follow to co-agglomerate in concentration. The successors are attracted by positive externalities associated with agglomeration. Marshall (1890) first hypothesized several sources of agglomeration economies stem from the concentration of manufacturing firms, including sharing intermediate suppliers, pooling labor markets, matching skills and localized transmission of ideas, technologies and information. Such agglomerative economies, known as the Marshall externalities, is notable in small and medium-sized manufacturing towns. Jacobs (1969) alternatively proposed the agglomeration externalities (Jacobs externalities) in big cities brought by cross-fertilization of ideas between different industries. Other sources of agglomeration economies, as discussed in Rosenthal and Strange (2004), include infrastructure sharing, home market effects, consumption advantage and rent seeking.

Depending on different specifications under an industrial scope, agglomeration can be distinguished into either localization and urbanization, or specialization and diversity. Localization and urbanization capture agglomeration externalities that stem from the absolute scale of agglomeration. In comparison, specialization and diversity address the structure of agglomeration. It should be pointed out that localization and urbanization are not mutually exclusive. Many large cities present both big urbanization agglomeration and localization agglomeration of certain industries at the same time. Similarly, a place can be diversified, but meanwhile specialize in one or a few industries.

The agglomeration theories suggest firms should form a concentration and take advantage of the sharing, matching and learning of resources and information. Empirical studies indeed reveal localization, urbanization, specialization and diversity all have positive impacts on the location choice of new firms (Head et al., 1995; Guimarães et al., 2000; Arauzo Carod, 2005; Jofre-Monseny et al., 2014; Niu et al., 2015). However, evidence on agglomeration impact on firm relocation within a metropolitan area is limited and mixed.

Early work of Schmidt (1979) reveals access to agglomeration economies is among the top concerns of firms in choosing alternative locations within metropolitan Denver. Erickson and Wasylenko (1980) focus on localization agglomeration and identify it has a positive role in firms choosing suburban locations in metropolitan Milwaukee. A positive impact of urbanization agglomeration is reported by de Bok and van Oort (2011), Weterings and Knoben, (2013) and Kronenberg (2013). In contrast, Cooke (1983) and Targa et al. (2006) find agglomeration economies lack explanatory power for firms' intra-metropolitan relocation. De Bok and Sanders (2005) even identify a negative impact of localization.

Previous studies suggest a much stronger impact of localization than urbanization on the location decision of new firms (Rosenthal and Strange, 2003,2005; Niu et al., 2015). For instance, Rosenthal and Strange (2003) find that adding one more worker to an industry attracts more new firms and workers in that industry than adding one more worker to other industries. However, literature does not discuss whether the more prominent impact of localization is also present in firm relocation.

Regarding specialization and diversity, Duranton and Puga (2001) propose a model of the life cycle of products and argue that a firm would have different location preference at different stages of its life cycle. The model assumes new firms have novel ideas but need time to operationalize them by experimenting with ideal production processes. A diversified environment is preferred at firm birth since it provides the opportunity to utilize cross-industry information, different production components and mixed-skills workers that are essential for starting a new business. Duranton and Puga report 58.6% of new French firms born in an employment area with above-median diversity between 1993 and 1996. Over time, some new firms failed, while others found ideal prototypes and relocated to cities that specialized in mass production. More than 60% of relocated firms left an employment area with above-median diversity and moved to an employment area with above-median specialization. The argument does not mean to undermine the attractiveness of specialization to new firms, rather it emphasizes the shift of location preference from diversity to specialization upon firm maturity.

Duranton and Puga's theory is supported by several empirical studies of inter-city firm relocations. In a Korean case study on how the relocation distance of firms is influenced by specialization and diversity, conducted by Hong (2014), manufacturing firms were found willing to bear the cost of long distance relocation (across-labor areas.) in exchange for higher specialization and lower diversity. This kind of location preference for specialization is more dominant in mature firms and big firms. Weterings and Knoben (2013) find when Dutch firms relocate, they would move to a location in the same municipality or labor market region if that municipality or region presents a high specialization and urbanization level. But they didn't consider the impact of diversity.

The discussion on the location preference of firms for specialization and diversity, however, is not conclusive. When specialization and diversity are considered simultaneously, Kronenberg (2013) shows both a high level of diversity and specialization are the underlying reasons a Dutch firm chooses a destination municipality during relocation, while the lack of diversity at origins is an important factor that pushes a firm to leave. De Bok and van Oort (2011) study firm intra-metropolitan relocations between postal code areas in a Dutch province of South-Holland.[33] Their results suggest that while specialization of postal code areas always draws relocated firms, some industries might also be attracted to postal code areas with a high level of diversity.

This essay seeks to fill the gap in literature by examining the determinant locational factors on firms making relocation choices within the Baltimore

[33] South-Holland is about half the size of the Baltimore Metropolitan Region in land area.

Metropolitan Region. It tries to compare the relative strength between localization and urbanization, and more importantly examine whether Duranton and Puga's theory holds for service firm's intra-metropolitan relocation.

4.3 Data, Facts and Variables

The primary dataset compiled in this essay is the National Establishment Time Serials (NETS) database. The NETS dataset records firms' location information detailed to city, zip code and the exact address depending on the availability. All of the firms belong to Division H (Finance, Insurance, and Real Estate) and Division I (Services) according to the Standard Industrial Classification (SIC) are defined as service firms.[34] To ensure minimal impacts of the Dot-com bubble and subprime financial crisis on relocation, this essay only studies firm relocations between January 2003 and January 2005.[35]

During the study period, there were 4,814 firm relocations that originated within the Baltimore Metropolitan Region, of which intra-metropolitan relocations took up about 91.5%. Nearly 58% of the relocations originated from the Baltimore Metropolitan Region are the relocation of service firms. Together, 2,548 service firm relocations are studied. As shown in Table 4.1, younger service firms (5 years old or younger) generated fewer relocations than the older company age group, 44.86% and 55.14% respectively. Younger firms are weak and some may not survive until the relocation takes place. The more mature firms are, the more likely they will reevaluate

[34] There are a total of 82 industry sectors under SIC's two digits classification. Service firms defined in this essay cover 21 of them.

[35] Although NETS does not report the exact relocation time, it identifies whether a firm moved between January 2003 and January 2004, or between January 2004 and January 2005.

the benefits and costs of their old location and make adjustments. Most relocated service firms are small. Small firms with five workers or less account for 75 % of all relocations. Compared to the small service firms' share of total firm stock in Baltimore Metropolitan Region, the relocated ones are a smaller proportion. Smaller firms are generally deemed to be more vulnerable and can more easily fail. Another possibility is that small firms, especially those that start as a sole proprietorship (i.e. family businesses or freelancers), register at residential locations and are less motivated to relocate. Speaking of the established category, standalone (non-subsidiary and non-chain) firm is the major firm type and generated the majority of relocations in Baltimore Metropolitan Region. Headquarters have a higher possibility of relocating than branch firms. Firm expansion has been long acknowledged as the number one reason for relocation (Pellenbarg, van Wissen and van Dijk, 2002), but it is not the key driver for firms initiating relocations in Baltimore Metropolitan Region.[36] Only 5.22% of relocated firms expanded their employment before relocation. Contrarily, 6.83% of firms declined in employment prior to relocations. The calculation of sales amount points to almost 25% of firms experienced growth but more declined, about 36% before relocation.

[36] The growth of firms is measured by employment and sales change one year before relocation.

Table 4.1 Description of Relocated Service Firms

Variable	Percent (%)	Variable	Percent (%)
Selected Characteristics of Relocated Firms		***General Geographic Pattern***	
Age		*Distance*	
Younger than or equal to 5	44.86	Within 1 mile	7.93
Older than 5	55.14	Within 5 miles	49.73
Size		Within 10 miles	77.08
Less than or equal to 5 workers	75.08	Within 15 miles	89.29
Less than or equal to 24 workers	93.45	*City-Suburbs*	
Less than or equal to 99 workers	98.39	From city to city	15.07
Establishment Category		From city to suburbs	11.85
Headquarter	4.43	From suburbs to city	6.63
Branch	3.02	From suburbs to suburbs	66.44
Standalone	92.54	*Center-Periphery*	
Growth Before Relocation		From center to same center	13.62
Employment increases	5.22	From center to different center	5.30
Employment decreases	6.83	From center to periphery	17.62
Sales increase	24.96	From periphery to center	14.13
Sales decrease	35.68	From periphery to periphery	49.33

Table 4.1 also reports a general geographic relocation pattern within the Baltimore Metropolitan Region.[37] About 50% of firms relocate to places within five miles of their origins and only less than 11% move more than 15 miles. About 27% of relocated firms came from Baltimore City but only 56% of them remained in the city after relocation. In contrast, 73% of relocated firms came from suburban counties and nearly 91% of these firms remained in the suburbs after relocation. However, this should not be interpreted as the evidence that Baltimore City is losing an attraction to relocated firms. It might be simply attributed to firms' preference for short-distance

[37] Should note that the results on relocation distance and center-periphery relocation pattern must be interpreted with caution since a portion of firms' addresses are approximated using centroid of street, census tracts or zip code areas.

movement and the geographic features of the Baltimore Region. As a small jurisdiction, Baltimore City is surrounded by large suburban counties. A relocating firm from Baltimore City will easily end in neighboring suburban counties even if they only move a few miles. The same short-distance movement of a suburban firm, however, is less likely to take the firm beyond the suburban boundary.

On relocation pattern between employment centers and periphery, Table 4.1 shows 52% of firms from employment centers remained in employment centers after relocation.[38] There were more firms moving away from centers than moving into centers. But the statistic alone does not undermine employment centers' attractiveness to relocating firms. Since centers occupy much smaller land areas compared periphery, at the same relocation distance, the possibility of a center-located firm moving beyond center boundaries is higher than the possibility of a periphery-located firm to move into a center.

The above discussion suggests general city-suburb and center-periphery relocation studies cannot fully explain the intra-metropolitan relocation pattern of service firms. This essay proposes use of the zip code area as the geographic unit for analysis. In the NETS dataset, firm addresses are most accurate at the zip code level. The number of zip code areas (192) in the Baltimore Metropolitan Region is also computationally applicable for a relocation study.[39] When assigning firms to zip code

[38] Employment centers are defined in the way as Chapter 3 does except using NETS data between 2003 and 2004.

[39] Shapefile of zip code areas was drawn from Maryland State Data Center, Maryland Department of Planning. For those cross-county zip code areas, they will be split and treated as different zip code areas. For instance, zip code area 21206 crosses the boundary between Baltimore City and Baltimore county, it is split into two zip code areas with 2451021206 defines the part of zip code area 21206 falls into Baltimore City and 2400521206 defines the part that falls into Baltimore county.

areas, only one firm moved to a place in the same zip code area of the same county; the rest of the firms either relocated to a different zip code area in the same residing county or a different zip code area in a different county.

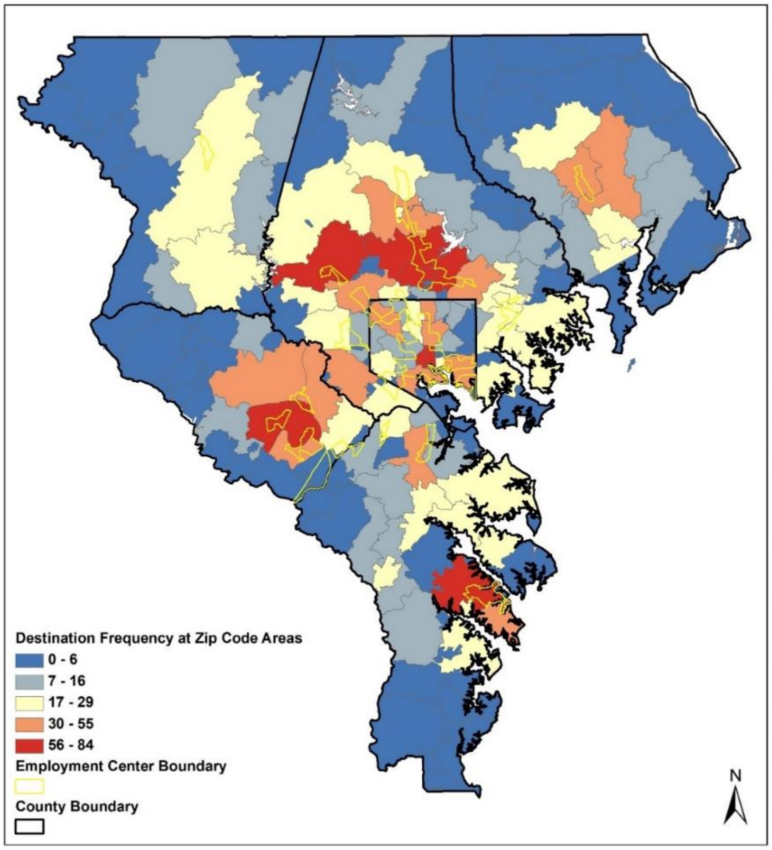

Figure 4.1 Destination Frequency of Relocation at Zip Code Areas

The geographic distribution of destination zip code choices based on the absolute number of relocated firms is shown in Figure 4.1. The spatial distribution of relocation density, the ratio of the relocation number to the total land area in each zip code area, is presented in Figure 4.2.[40] Both figures reveal the main hot destination spots are the Columbia area in Howard County, Glen Burnie area and Severna Park-

[40] Data in Figure 4.1 is classified and presented based on Jenks natural breaks; while data in Figure 4.2 is classified and presented based on quantile breaks.

Annapolis coastal area in Anne Arundel County, Bel Air area in Harford County, Towson area in Baltimore County adjacent to the upper fringe of Baltimore City and the city itself, all of which are more developed rich suburban areas in the region except for Baltimore City. Almost all hot destination spots are overlapped with the employment centers, indicating employment centers are preferred relocation destinations.

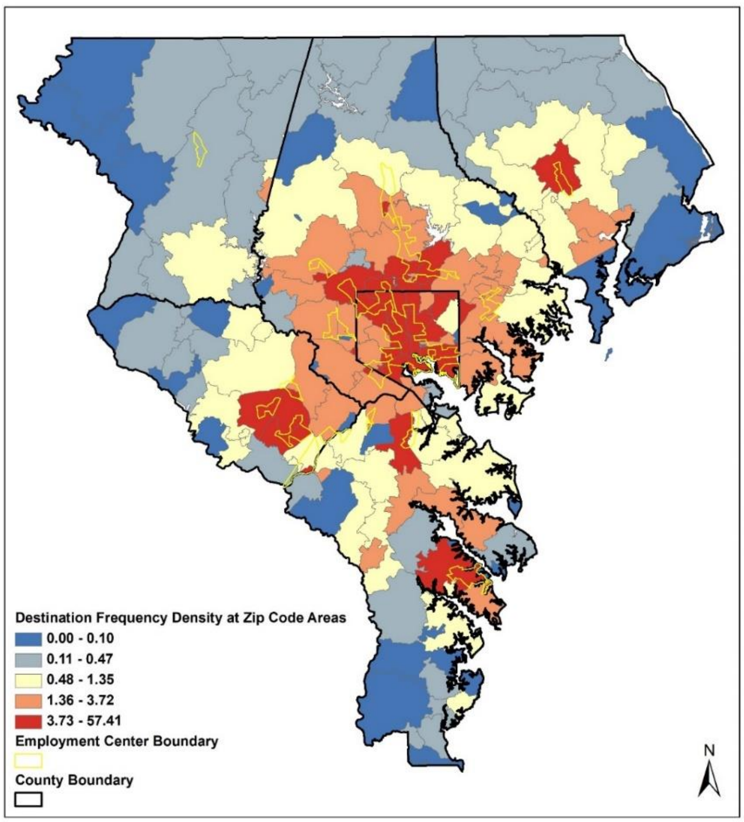

Figure 4.2 Density of Destination Frequency at Zip Code Areas

The focus of the essay is the impact of agglomeration on relocation. All agglomeration indicators are measured at zip code level using NETS data.[41]

[41] Firm's own employment is excluded in all agglomeration related calculations.

Localization and urbanization are measured respectively by either employment or employment density of the same industry and other industries in a zip code area. [42] The Herfindahl-Hirschman Index (HHI) index is calculated following the conventional way as $\sum_{j}^{82} {S_{jk}}^2$, where S_{jk} is the employment share of industry j in zip code area k. Diversity then is proxied by $1 - \sum_{j}^{82} {S_{jk}}^2$. Location quotient (LQ) of a zip code area is used to measure specialization. The equation of LQ for firm i in industry j in zip code area k is given by $LQ_{ijk} = \frac{E_{ijk}/E_{ik}}{E_{ij}/E_i}$, where E_{ijk} is the number of workers in industry j in zip code area k, E_{ik} is the number of workers in all industries in zip code area k, E_{ij} is the number of workers in industry j in the Baltimore Metropolitan Region, and E_i is the number of workers in all industries in the Baltimore Metropolitan Region.

Table 4.2 Diversity and Specialization of Origins and Destinations

		Destination Specialization			Destination Diversity		
		Below Median	Above Median	Total	Below Median	Above Median	Total
			A			C	
Origin Diversity	Below Median	7.14%	20.49%	27.63%	7.26%	20.37%	27.63%
	Above Median	21.19%	51.18%	72.37%	16.60%	55.77%	72.37%
	Total	28.34%	71.66%	100.00%	23.86%	76.14%	100.00%
			B			D	
Origin Specialization	Below Median	9.54%	17.39%	26.92%	6.87%	20.05%	26.92%
	Above Median	18.80%	54.28%	73.08%	16.99%	56.08%	73.08%
	Total	28.34%	71.66%	100.00%	23.86%	76.14%	100.00%

[42] For firms that changed industry during relocation, localization and LQ is measured/calculated based on the industry they choose after relocation. When localization is not included in the model, an urbanization indicator will be measured by total employment of a zip code area.

Table 4.2 provides a preliminary investigation of a relocated firms' preference for specialization and diversity. Zip code areas are categorized into with below-median/above-median diversity, and with below-median/above-median specialization of according industries. Compared to Durantan and Puga's calculation for inter-city relocation, NETS presents a much smaller percentage of relocated firms originated from locations with above-median diversity and moved to locations with above-median specialization for intra-metropolitan relocations in the Baltimore Metropolitan Region.[43] It shows that about 72% of relocations departed from zip code areas with above-median diversity, and 70% of those relocations ended up in zip code areas with above-median specialization. In other words, only about 51% of relocated service firms moved from a zip code area with above-median diversity to a zip code area with above-median specialization. In the meantime, there are about 56% of relocated service firms that moved from a zip code area with above-median diversity to a zip code area with above-median diversity; about 56% of relocated service firms moved from a zip code area with above-median specialization to a zip code area with above-median diversity; and about 54% of relocated service firms moved from a zip code area with above-median specialization to a zip code area with above-median specialization. One explanation for this relocation pattern is that a zip code area can be both diversified and specialized. More than 56% of relocated firms originated from and relocated to a zip code area with above-median diversity and above-median specialization at the same time. The Baltimore findings supplement Duranton and Puga's (2000, 2001) sole

[43] Duranton and Puga (2000, 2001) in their inter-city relocation analysis show 94% of all relocations originated from employment areas with above-median diversity, and about 76% to 82% of relocated services firms left an employment area with above-median diversity to an employment area with above-median specialization.

finding on inter-city relocating firms' movement from diversity to specialization by adding evidence of intra-metropolitan relocating firms' movement between diversity and specialization (i.e., from diversity to specialization and vice versa; diversity to diversity; and specialization to specialization).

Besides agglomeration indicators, a set of other zip code area-specific variables is included in the estimation. Demographic information is drawn from 2000 U.S. decennial census data. Population data at block group level is aggregated into zip code areas. Population density and percentage of age 25 and older population with bachelor or higher degrees are calculated. The relocation distance is proxied by the Euclidean distances between centroids of zip code areas. Land stock is estimated with 2002 Land Use & Cover map created by the Maryland Department of Planning. All types of urban use land within a zip code area are considered as potential places that allow the operation of service firms.[44] The impact of employment centers is captured by a center share index which is calculated by employment center area in a zip code area dividing the total land area of that zip code.

Wage data is acquired from Census Business Pattern which provides payroll information on Zip Code Tabulation Areas. Since commercial rent data is not available, the average commercial unit property value of a zip code area is used to proxy the rental cost. Data of commercial property value is taken from the Maryland Property View Data 2003/2004. Both wage and property value are converted to 2000 U.S. dollars.

[44] Although headquarters and branches may only locate at commercial properties, standalone firms especially sole proprietorships might register at residential and even industrial properties, which makes all types of urban uses land potential relocation destinations.

Previous studies show property tax influence a firm's location choice within a metropolitan area (Charney, 1983; Finney, 1994). A high tax rate daunts the entering of new and incumbent firms, in contrast to tax incentives and fiscal subsidies that attract firms to locate and distort firms' intention of maximizing "pure" economic profit solely through production activities. In this essay, the property tax rate is aggregated at zip code level. Each tax territory that overlaps with a target zip code area is assigned with a weighted property tax rate by multiplying the real tax rate with the land share of the zip code area of that tax territory. The sum of all overlapped tax territories' weighted property tax rate is used to form the applied property tax rate for the target zip code area.

Impacts of transportation accessibility on location choice vary by firms in different industries. It is found that manufacturing plants favor locations near train stations, airports, piers and major highways, while service firms prefer sites close to both subway/train stations and highways (Holl, 2004; de Bok and van Oort, 2011; Nguyen et al., 2012). Considering that, the accessibility of a location is measured in two ways. First, the distance from the centroid of a zip code area to the nearest highway ramp is calculated as a proxy of accessibility to the highway. Second, two variables are created to measure the accessibility to transit rail stations. The density of Baltimore Metro and Light Rail stations is calculated by dividing the number of Baltimore Metro and Light Rail stations in a zip code area by the land area of that zip code area. Similarly, the density of a Maryland Area Rail Commuter (MARC) train station is calculated by dividing MARC train station quantities in a zip code area by the land area of that zip code area. Competition within a zip code area is measured in line with Glaeser et al.

(1992). The competition within a firm's own industry is measured by the number of firms per worker of its own industry in a zip code area relative to the number of firms per worker of its own industry in the whole region. And the competition outside its own industry is measured by the number of firms per worker of other industries in a zip code area relative to the number of firms per worker of other industries in the whole region.

In addition, some firm-specific variables are also considered. The variables include a firm's age, size, growth, establishment category and density preference. Firm size is measured by number of employment, growth is calculated by change in sales in the previous year of relocation, establishment category is a dummy variable which equals 1 if the relocated firm is a headquarters or a branch, and finally density preference is presented by population density of the zip code area where a firm is originated from.

4.4 Empirical Methodology and Findings

4.4.1 Methodology

Discrete choice model is widely adopted in the study of firm location choice. Conventional multinomial logit and conditional logit model assume all location-specific information is observed, so the odds ratio of any two locations should be independent to the addition or deletion of any other location. This assumption is known as the independence of irrelevant alternatives (IIA). However, it is challenging to hold the IIA assumption in real life studies. For instance, deleting a zip code area in Baltimore City would cause different changes in the probability a firm chooses another zip code area in the city and the possibility it chooses some zip code area in suburban counties. Given that, a nested logit model is applied in this essay as it reconciles the

IIA assumption and allows correlation between alternatives within a nest (Bhat, Paleti and Singh, 2014). It assumes that some random shocks make a firm choose a nest and then choose an alternative location from that nest.

The construction of a clear nesting structure always lies at the heart of the nested logit model application. Learned from the way Strauss-Kahn and Vivas (2009) specify nesting structure for their inter-metropolitan firm relocation study, nesting structure in this essay is set up based on county and population density. [45] The choice of county nest is mainly driven by the widely-accepted recognition that county as an administrative unit is more relevant to and decisive in policy-making, planning development and implementation, shaping firms' decisions in locating in the respective jurisdictions (Bhat, Paleti and Singh, 2014). Population density nest is also appropriate as population density is associated with local demand and infrastructure level, both of which are important for the success of service firms.

In the county-nested model, a firm chooses a county to relocate in the first stage and selects among the alternative zip code areas within the chosen county in the second stage. Similarly, in the population density-nested model, a firm chooses a density category of zip code areas it intends to relocate in the first stage and selects a zip code area from that density category in the second stage. It should be noted that although the selection of a zip code area is divided into two stages, there is no temporal ordering (Hensher et al., 2015).

[45] Strauss-Kahn and Vivas (2009) set up the second nesting structure based on population of metropolitan areas. Here population density is used as in most intra-metropolitan relocation studies.

A simplified mathematic presentation of the nested logit model is described below. A firm chooses a location for the utility it provides. Under random-utility model, the utility U_{ij} provided by zip code area j in county/population density nest k for firm i can be expressed as

$$U_{ij} = V_{ij} + \varepsilon_{ij} = z_i\alpha_j + x_{ij}\beta_j + \varepsilon_{ij}, \tag{1}$$

where V_{ij} is the deterministic part and ε_{ij} is the random part following the generalized extreme value (GEV) distribution. x_{ij} includes zip code area-specific variables and z_i denotes firm-specific variables. The expected value of the utility that firm i obtains by choosing a zip code area in nest k is called inclusive value (IV_k), which is given by

$$IV_k = ln \sum_{j \in A_k} \exp(V_j/\tau_k), \tag{2}$$

where A_k is the set of alternative zip code areas in nest k. τ_k is the dissimilarity parameter. It is calculated by $\tau_k = \sqrt{1-\rho_k}$. Here ρ_k represents the correlation between alternatives in nest k. The probability firm i choose zip code area j in nest k then is

$$\mathrm{Pr}_j = \frac{\exp(V_j/\tau(j))}{\exp(IV(j))} \frac{\exp(\tau(j)IV(j))}{\sum_k \exp(\tau_k IV_k)}. \tag{3}$$

In the above Eq. (3), $\tau(j)$ and $IV(j)$ are the dissimilarity parameter and inclusive value for which the nest j belongs. As specified in Eq. 3, the nested logit model detects the joint probability of choosing county/population density nest k and zip code area j conditional on choosing nest k.

4.4.2 Basic estimation

The result of the basic estimation is presented in Table 4.3. Before fitting into the nested logit model, the data is estimated by a conditional logit model with the result presented in Column 1. Column 2 and Column 3 show the estimates of the county-nested model and population density-nested model, respectively. Column 4 and Column 5 alternatively give estimates of the county-nested model and population density-nested model with standardized independent variables to better capture the importance of each independent variable. The χ^2 of Likelihood-ratio test for IIA shown at the bottom of Table 4.3 suggest a rejection of IIA, so a nested logit specification should be warranted. The essay also runs the conditional logit model with an omitted set of alternatives and examines the consistency of estimates using Hausman's specification test. If IIA holds, omitting subset from the conditional logit model should not cause inconsistent estimates. As expected, the Hausman test rejects IIA. These tests, however, only confirm the nested structure exists without evaluating whether the selected nested structure is correct. For an appropriate nested structure, the dissimilarity parameters should be smaller than 1 under random-utility model (Cameron and Trivedi, 2005). Only Column 3 gives consistent estimates as it is the only model in Table 4.3 that has dissimilarity parameters all smaller than 1.

Table 4.3 Neighborhood Characteristics and Service Firm Intra-Metropolitan Relocation

	(1)	(2)	**(3)**	(4)	(5)
Diversity	4.724***	4.788***	**3.461*** **	0.914***	0.831***
	(0.390)	(0.497)	**(0.402)**	(0.093)	0.083
Location quotient	0.043***	0.049***	**0.035*** **	0.091***	0.075***
	(0.006)	(0.007)	**(0.006)**	(0.014)	0.012
Total employment	1.60E-05***	1.37E-05***	**1.10E-05*** **	0.185***	0.191***
	(1.74E-06)	(2.17E-06)	**(1.57E-06)**	(0.029)	0.024
Population density	1.34E-05	3.16E-05***	**1.40E-06**	0.112***	0.049
	(1.12E-05)	(1.18E-05)	**(1.03E-05)**	(0.041)	0.046
Percentage of population 25 years or	1.183***	1.778***	**0.988*** **	0.289***	0.174***
above with bachelor's degree or higher	(0.154)	(0.192)	**(0.132)**	(0.030)	0.025
Relocation distance	-0.186***	-0.191***	**-0.146*** **	-2.202***	-1.983***
	(0.004)	(0.005)	**(0.008)**	(0.060)	0.086
Urban land area	0.090***	0.113***	**0.088*** **	0.444***	0.388***
	(0.006)	(0.009)	**(0.007)**	(0.035)	0.030
Center area share	0.201	0.071	**0.048**	0.010	0.016
	(0.146)	(0.161)	**(0.115)**	(0.038)	0.034
Wage	-1.11E-05***	-1.11E-05***	**-5.46E-06***	-0.107***	-0.071**
	(3.34E-06)	(4.00E-06)	**(2.85E-06)**	(0.040)	0.033
Commercial property value	2.59E-03***	3.15E-03***	**2.40E-03*** **	0.214***	0.168***
	(5.72E-04)	(6.54E-04)	**(4.82E-04)**	(0.043)	0.038
Property tax rate	-0.060	0.053	**0.091**	0.211*	0.024
	(0.081)	(0.268)	**(0.064)**	(0.121)	0.041
Distance to highway ramp	0.053***	-0.009	**0.037*** *	-0.020	0.085**
	(0.017)	(0.021)	**(0.015)**	(0.050)	0.042
Metro and Light Rail station density	0.046	0.015	**0.004**	0.008	0.021
	(0.039)	(0.045)	**(0.033)**	(0.043)	0.037
MARC station density	-0.265*	-0.165	**-0.053**	-0.025	-0.021
	(0.153)	(0.177)	**(0.127)**	(0.031)	0.027
Competition within industry	-0.008	-0.011	**-0.003**	-0.029	-0.011
	(0.013)	(0.015)	**(0.010)**	(0.039)	0.032
Competition outside industry	-0.324***	-0.411***	**-0.231*** **	-0.521***	-0.377***
	(0.051)	(0.061)	**(0.046)**	(0.076)	0.067

Table 4.3 Neighborhood Characteristics and Service Firm Intra-Metropolitan Relocation (continue)

	(1)	(2)	(3)	(4)	(5)
Dissimilarity parameter (τ)					
Anne Arundel County		1.208		1.149	
		(0.057)		(0.043)	
Baltimore County		1.103		1.211	
		(0.046)		(0.055)	
Carroll County		1.721		1.542	
		(0.104)		(0.097)	
Harford County		1.331		1.467	
		(0.080)		(0.077)	
Howard County		1.113		1.102	
		(0.060)		(0.057)	
Baltimore City		0.936		0.951	
		(0.089)		(0.089)	
PopDen_1			0.820		1.052
			(0.075)		(0.087)
PopDen_2			0.859		0.887
			(0.071)		(0.064)
PopDen_3			0.842		0.968
			(0.054)		(0.054)
PopDen_4			0.770		0.914
			(0.047)		(0.044)
PopDen_5			0.804		1.045
			(0.052)		(0.046)
PopDen_6			0.648		0.926
			(0.055)		(0.054)
Number of observations	489216	489216	489216	489216	489216
Log likelihood	-9879.0533	-9758.447	-9785.9584	-9764.6873	-9810.1
LR χ^2	7034.09				
Pseudo R^2	0.2625				
Number of cases		2548	2548	2548	2548
Wald χ^2		1956.58	919.36	1990.71	982.58
LR test for IIA χ^2		88.88	42.3	78.65	49.55

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses. Coefficients of firm-specific variables are not reported to conserve space.

The interpretation of the results focuses on location-specific features. Estimates of nested logit model do not vary significantly from that of the conditional logit model. The coefficients of variables in the county-nested model are bigger in absolute value than the coefficients of variables in population density-nested model, suggesting that there is a larger variance of locational attributes between zip code areas within a county nest than between zip code areas within a population density nest. Agglomeration indicators consistently have significant and positive coefficients in all models, which means agglomeration economies matter at smaller geographic units like zip code areas. Overall, firms are attracted by both diversity and specialization when choosing alternative locations in the same metropolitan area. This does not entirely follow Duranton and Puga's life cycle products theory, rather it is in line with the empirical findings of de Bok and van Oort (2011) and Kronenberg (2013). A firm's value for low production cost provided by industry specialization does not diminish its cherishing of the diversified demand and cross-industry ideas, technologies and information. This essay does not obtain a conclusive result regarding whether specialization or diversity matters more on relocation since the estimates in Column 4 and Column 5 are not consistent. However, the magnitude differences between the estimates of *diversity* coefficient and *location quotient* coefficient in those two models suggest a high possibility of diversity effect overwhelms specialization effect. The main explanation of the higher possibility of finding a stronger diversity impact on a service firm's relocation choice are: (1) service firm's lower labor and intermediate goods intensive features make them relatively less sensitive to specialization; (2) considering the changing demand for services is much quicker than the changing demand for manufacturing products, a diversified location can keep a service firm's pace with the fast-changing demand of their consumers by offering cross-industry interactions.

The positive coefficient of *total employment* in a zip code area indicates the existence of attractions to relocating service firms generated from agglomeration economies based on the absolute scale of concentration. It should be noted that the impact of urbanization agglomeration could also be partially picked up by the population density of a zip code area[46]. In Table 4.3, the coefficient of *population density* is positive and significant in a county-nested model but not in a population density-nested model. Demands may vary greatly between zip code areas in the same county, but they are likely to be close between zip code areas within the same population density nest.

Table 4.4 presents a more comprehensive examination of agglomeration impact by applying different agglomeration indicators in the model. All models of Table 4.4 use population density-nested structure with unstandardized data to report consistent estimates. Column 1 in Table 4.4 shows that when the total employment variable is excluded, the impact of urbanization agglomeration is captured by *population density*, and diversity and specialization coefficients remain positive and statistically significant. A similar result is reported in Column 2 when total employment is replaced by total employment density. Column 3 and Column 4 explore the influence of localization agglomeration and compare its strength to urbanization agglomeration. To prevent collinearity between agglomeration variables, a *location quotient* variable is not included in both models. Estimates of the localization indicator and urbanization indicator are both positive and significant.

[46] By construction, total employment better captures the demand of firms, while population density better captures the demand of residents.

Table 4.4 Estimation of Intra-Metropolitan with Different Agglomeration Indicators

	(1)	(2)	(3)	(4)
Diversity	3.953***	3.976***	3.458***	3.911***
	(0.439)	(0.440)	(0.398)	(0.434)
Location quotient	0.037***	0.037***		
	(0.006)	(0.006)		
Total employment density		2.56E-06		
		(2.40E-06)		
Own-industry employment			7.87E-05***	
			(1.09E-05)	
Other-industry employment			7.88E-06***	
			(1.54E-06)	
Own-industry employment density				8.03E-06*
				(4.70E-06)
Other-industry employment density				2.22E-06
				(2.42E-06)
Population density	3.30E-05***	2.82E-05***	4.45E-06	2.83E-05***
	(8.98E-06)	(1.01E-05)	(1.01E-05)	(9.99E-06)
Percentage of population 25 years or above with bachelor's degree or higher	1.078***	1.092***	0.941***	1.110***
	(0.136)	(0.136)	(0.131)	(0.136)
Relocation distance	-0.148***	-0.148***	-0.145***	-0.147***
	(0.008)	(0.008)	(0.008)	(0.008)
Urban land area	0.107***	0.107***	0.087***	0.106***
	(0.007)	(0.007)	(0.007)	(0.007)
Center area share	0.091	0.076	0.047	0.077
	(0.111)	(0.111)	(0.113)	(0.111)
Wage	3.41E-06	2.32E-06	-4.94E-06*	3.00E-06
	(2.49E-06)	(2.70E-06)	(2.83E-06)	(2.68E-06)
Commercial property value	2.33E-03***	2.27E-03***	2.36E-03***	2.20E-03***
	(4.83E-04)	(4.85E-04)	(4.77E-04)	(4.82E-04)
Property tax rate	0.056	0.068	0.089	0.066
	(0.062)	(0.063)	(0.063)	(0.063)
Distance to highway ramp	0.032**	0.030**	0.038**	0.029*
	(0.016)	(0.016)	(0.015)	(0.015)
Metro and Light Rail station density	0.080***	0.052	0.005	0.049
	(0.028)	(0.037)	(0.032)	(0.037)
MARC station density	-0.138	-0.097	-0.088	-0.085
	(0.113)	(0.117)	(0.126)	(0.117)
Competition within industry	-0.009	-0.009	-6.25E-04	-0.019
	(0.011)	(0.011)	(9.77E-03)	(0.012)
Competition outside industry	-0.327***	-0.325***	-0.218***	-0.298***
	(0.050)	(0.049)	(0.045)	(0.048)
Number of observation	489216	489216	489216	489216
Number of cases	2548	2548	2548	2548
Log likelihood	927.1	925.72	921.71	923.91
Wald $\chi2$	-9816.72	-9816.15	-9775.08	-9826.68
LR test for IIA $\chi2$	60.77	58.95	46.42	59.4

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses. Dissimilarity parameters in all models are smaller than 1. Coefficients of firm-specific variables and dissimilarity parameters are not reported to conserve space.

Previous studies found that the localization effect is more important than the urbanization effect on a firm's birth and productivity growth (Henderson, 2003; Rosenthal and Strange, 2003). The essay indicates that the advantage of localization is also extended to a firm's intra-metropolitan relocation as the coefficient of the localization indicator is about one order of magnitude larger than the coefficient of an urbanization indicator in Column 3. Table 4.4 also implies the absolute scale of agglomeration matters more than the relative scale of agglomeration on intra-metropolitan relocation. When localization and urbanization indicators are measured by density of employment, Column 4 shows the coefficient of *own-industry employment density* is significant at the least rigorous 10% significance level. The coefficient of the *other-industry employment density* variable is not statistically significant.

The Basic Estimation also provides an understanding of other related locational determinants that matter to service firms' relocation choices. Interpreted from the positive and significant coefficients of education level variable, service firms are very likely to be attracted to a zip code area concentrated with a highly educated population. A zip code area with high-level human capital can benefit service firms, especially those in business, legal, finance and insurance sectors, by providing a sufficient pool of more qualified labor force and creating a more diversified demand for the service goods compared to a zip code area with low-level human capital. The significant and negative estimate of *relocation distance* indicates that even within a metropolitan area, firms would like to reduce relocation distance to save searching and moving costs and retain consumers and their network. Firm relocation choice is also bounded by the supply of different land uses. Firms are predicted to have a higher probability to relocate to a zip code area with a larger stock of urban use land area. Although employment centers affect firm birth and survival, they do not show statistically significant impact on intra-metropolitan relocation at least for service firms. Employment centers only obtain positive and significant coefficients when other agglomeration indicators are omitted from the model[47]. Under that condition, it is safe to assume that the impact of agglomeration in my examination is fully captured by other agglomeration indicators instead of employment centers.

The average wage of a zip code area is reported to have a generally significant but limited impact on service firm relocations. Wage is an indicator of the labor costs in the destination area. Reasonably, firms would relocate to places with lower wages. But the estimates are only significant at a 10% significance level. The coefficient of *commercial property value* has an unexpected positive sign. Two possible explanations are offered. On one hand, service firms are less dependent on office size. When the commercial office cost (i.e. rent) is high, they can pack themselves into more compact spaces or quit office renting (like some sole proprietorships register in residential locations). On the other hand, high property value usually is associated with high amenity level that attracts relocation. The estimation does not reveal a significant impact of property tax rate on intra-metropolitan service firm relocations. This suggests locational disincentives from property taxes are less relevant to service firms given their small average size (Charney, 1983; Finney, 1994). Also worth noting is that the

[47] Estimates are available upon request.

disincentives of property taxes can be neutralized if they are spent on promoting the local business environment.

In the population density-nested model, accessibility to a highway ramp is projected to be negatively associated with the probability of a service firm settling down in that location. As service firms are involved more in the transportation of people than the transportation of goods, it is possible they may not have as high a demand for highway accessibility as manufacturing firms. Rather, traffic congestion is aggravated when approaching the highway ramps so highway accessibility daunts a firm's entry. The accessibility to train stations is not a significant determinant of intra-metropolitan relocation. Despite the increasing advocacy for transportation oriented development by planners, firms still are more likely to follow agglomeration rather than transportation accessibility.

Coefficients of competition indicators obtain negative sign as expected. But only *competition from other industries* coefficients are statistically significant. According to firm survival literature, ceteris paribus, competition outside industries endanger firms in more harmful ways so it deters firms from entering.

4.4.3 Robustness Check

The essay provides estimation results by firms' agglomeration preference, age and establishment type for robustness checks. As shown in Table 4.5, the estimates of firms that are from zip code areas with above-median diversity have no big differences from their cohorts from zip code areas with above-median specialization, or from the basic results in Table 4.3 except for wages. Wage doesn't present significant impact on relocation choice of firms from zip code areas with above-median diversity but reduces the probability of relocations of firms from zip code areas with above-median specialization. The check on young firms (age ≤5) and old firms (age ≥6) is presented in Table 4.6. Both structure and scale of agglomeration matter to young and old firm's relocation decision making. Moreover, it appears old firms appreciate more the structure of agglomeration while young firms value more the scale of agglomeration. It is worth pointing out that the coefficients of wage, property tax and highway accessibility are only significant for young firms. One explanation is that young firms are relatively weak so are more sensitive to the amenities of alternative locations.

Based on establishment type, I categorize firms into three groups: headquarters and branches, sole proprietorships (assumed here to be standalone firms with only one worker), and other standalone firms for robustness check. The estimation results are given in Table 4.7. For headquarters and branches, only the coefficient of *diversity* is statistically significant. Specialization and urbanization might have a critical influence on the location choice of headquarters and branches between metropolitan areas (as shown in Strauss-Kahn and Vivas (2009) for headquarters), they do not matter for the intra-metropolitan relocations.

Table 4.5 Estimation of Intra-Metropolitan Relocation of Firms Depart from Above Median Diversity or Above Median Specialization

	Above median diversity	Above median specilization
	(1)	(2)
Diversity	3.465***	3.554***
	(0.464)	(0.484)
Location quotient	0.036***	0.040***
	(0.006)	(0.006)
Total employment	1.24E-05***	1.21E-05***
	(1.88E-06)	(1.87E-06)
Population density	-3.49E-06	-3.79E-06
	(1.24E-05)	(1.24E-05)
Percentage of population 25 years or above with bachelor's degree or higher	0.763***	1.004***
	(0.148)	(0.156)
Relocation distance	-0.137***	-0.144***
	(0.009)	(0.009)
Urban land area	0.083***	0.084***
	(0.007)	(0.008)
Center area share	0.145	-0.025
	(0.138)	(0.136)
Wage	-4.84E-06	-6.69E-06**
	(3.29E-06)	(3.35E-06)
Commercial property value	2.63E-03***	2.34E-03***
	(5.60E-04)	(5.70E-04)
Property tax rate	0.001	0.087
	(0.079)	(0.076)
Distance to highway ramp	0.042**	0.037**
	(0.017)	(0.018)
Metro and Light Rail station density	0.019	0.018
	(0.037)	(0.040)
MARC station density	-0.116	-0.130
	(0.145)	(0.157)
Competition within industry	-0.005	0.003
	(0.012)	(0.010)
Competition outside industry	-0.186***	-0.272***
	(0.051)	(0.056)
Number of observation	354048	357504
Number of cases	1844	1862
Log likelihood	-7107.3922	-7054.7791
Wald χ^2	645.34	657.21
LR test for IIA χ^2	33.5	34.78

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses. Dissimilarity parameters in all models are smaller than 1. Coefficients of firm-specific variables and dissimilarity parameters are not reported to conserve space.

Table 4.6 Estimation of Intra-Metropolitan Relocation by Firm Age

	Age<=5	Age>5
	(1)	(2)
Location quotient	0.029***	0.039***
	(0.007)	(0.009)
Diversity	2.779***	3.862***
	(0.515)	(0.587)
Total employment	1.32E-05***	8.10E-06***
	(2.29E-06)	(2.19E-06)
Population density	-4.66E-06	7.26E-06
	(1.38E-05)	(1.49E-05)
Percentage of population 25 years or above with	0.827***	1.159***
bachelor's degree or higher	(0.178)	(0.196)
Relocation distance	-0.124***	-0.170***
	(0.011)	(0.012)
Urban land area	0.085***	0.095***
	(0.011)	(0.010)
Center area share	-0.122	0.153
	(0.157)	(0.164)
Wage	-6.78E-06*	-3.18E-06
	(3.94E-06)	(4.06E-06)
Commercial property value	0.002***	0.002***
	(0.001)	(0.001)
Property tax rate	0.203**	-0.017
	(0.085)	(0.093)
Distance to highway ramp	0.043**	0.030
	(0.020)	(0.023)
Metro and Light Rail station density	-0.041	0.034
	(0.053)	(0.044)
MARC station density	0.025	-0.073
	(0.205)	(0.167)
Competition within industry	0.002	-0.007
	(0.012)	(0.016)
Competition outside industry	-0.120**	-0.346***
	(0.057)	(0.072)
Number of observation	219456	269760
Number of cases	1143	1405
Log likelihood	-4433.32	-5302.2223
Wald χ^2	369.18	530.93
LR test for IIA χ^2	32.13	23.04

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses. Dissimilarity parameters in all models are smaller than 1. Coefficients of firm-specific variables and dissimilarity parameters are not reported to conserve space.

For standalones, specialization, diversification and urbanization are all important determinants. It is worth noting that both the magnitude and statistical significance of specialization and urbanization coefficients are much smaller for sole proprietorships, as defined here. Sole proprietorships are assumed to not hire employees, so they take limited advantage of labor pooling and matching. The same reason also explains wage as an insignificant determinant for the relocation of sole proprietorships, as defined. Furthermore, we assume for this purpose that a self-employed entrepreneur or freelancer does not have to rent offices. This makes sole proprietorships also care less about property tax and highway accessibility. The zero labor and rent costs also minimize the negative impact of competition from other firms on the relocation of sole proprietorships.

A challenge to location studies based on smaller geographic areas is the existence of spatial dependence among neighboring location alternatives (de Bok and van Oort, 2011). Theoretically, the more proximate two locations are, the higher the possibility that one location's attractiveness is affected by the other one. The magnitude of spatial dependence also relies on the geographic pattern of social interactions, trade, factor movements and so on. Regarding agglomeration externalities, labor sharing, skill matching and knowledge spillover could exist within a metropolitan area. This means the agglomeration at one location of the metropolitan area should generate some agglomeration economies for all firms located in that metropolitan area. The chance of a location being selected is not solely determined by its own agglomeration level but also the agglomeration level at all other alternative locations in the metropolitan area.

Table 4.7 Estimation of Intra-Metropolitan by Establishment Category

	Headquarters and branches	Sole proprietorship	Standalones except sole proprietorship
	(1)	(2)	(3)
Diversity	5.578***	3.075***	3.446***
	(2.101)	(0.718)	(0.497)
Location quotient	0.036	0.022**	0.066***
	(0.043)	(0.009)	(0.013)
Total employment	3.11E-06	7.14E-06**	1.36E-05***
	(5.60E-06)	(2.86E-06)	(2.04E-06)
Population density	3.33E-06	2.28E-05	-9.76E-06
	(3.77E-05)	(1.88E-05)	(1.34E-05)
Percentage of population 25 years or above with bachelor's degree or higher	1.133**	0.860***	1.019***
	(0.566)	(0.241)	(0.164)
Relocation distance	-0.171***	-0.126***	-0.152***
	(0.038)	(0.015)	(0.010)
Urban land area	0.069**	0.090***	0.090***
	(0.028)	(0.014)	(0.008)
Center area share	0.569	-0.159	0.040
	(0.458)	(0.210)	(0.145)
Wage	1.45E-05	-2.89E-06	-9.71E-06***
	(1.16E-05)	(5.08E-06)	(3.67E-06)
Commercial property value	0.004**	0.002***	2.29E-03***
	(0.002)	(0.001)	(6.24E-04)
Property tax rate	-0.070	0.144	0.095
	(0.270)	(0.113)	(0.081)
Distance to highway ramp	0.143**	0.018	0.038**
	(0.071)	(0.027)	(0.019)
Metro and Light Rail station density	-0.032	-0.086	0.023
	(0.097)	(0.074)	(0.041)
MARC station density	-0.231	0.032	-0.062
	(0.356)	(0.277)	(0.157)
Competition within industry	-0.085	0.016	0.006
	(0.062)	(0.020)	(0.012)
Competition outside industry	-0.628**	-0.128*	-0.265***
	(0.259)	(0.075)	(0.058)
Number of observation	36480	125760	326976
Number of cases	190	655	1703
Log likelihood	-646.138	-2609.43	-6457.54
Wald χ^2	78.46	212.62	630.39
LR test for IIA χ^2	16.32	14.61	29.04

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses. Dissimilarity parameters in all models are smaller than 1. Coefficients of firm-specific variables and dissimilarity parameters are not

Yet the most important impact of agglomeration still comes from the agglomeration at the chosen location. The Study of Rosenthal and Strange (2003) showed the agglomeration effect within a one-mile distance buffer of a firm might be 10 times that of the agglomeration effect beyond that distance. Some sources of agglomeration economies may attenuate even faster. By studying the location choice of advertisement agencies in Manhattan, Arzaghi and Henderson (2008) found the benefits of knowledge spillovers and networking with nearby agencies declined by 80% when two firms are 500-meters apart and ran out after roughly a half mile away.

To assess how spatial dependence affects the estimation of agglomeration indicators and other locational determinants, the essay separately examines firm relocation within suburban counties of Baltimore Metropolitan Region. Zip code areas in the suburbs are much bigger than those in Baltimore City. The average size of zip code areas in the suburbs is 13.45 square miles, which is 5.3 times that of Baltimore City. The large land area of a zip code area reduces the impact of its locational factors, especially agglomeration, on firm relocation choice to another zip code area. A summary of the regression results is presented in Table 4.8. Most coefficients have the same sign and significance as in the Basic Estimation. The magnitude of specialization coefficient declines slightly, while the magnitude of diversity and urbanization coefficients increase considerably. Other notable differences include: wage is no longer significant even at 10% significance level and MARC train station appears to reduce relocation possibility. A plausible explanation to the change of MARC station estimate is that more than half of MARC stations in the suburbs are located at places concentrated with manufacturing firms and warehouses, which are not suitable for service firms.

Table 4.8 Estimation of Relocation within Suburban Counties

Diversity	4.656***
	(0.620)
Location quotient	0.031***
	(0.007)
Total employment	1.60E-05***
	(2.28E-06)
Population density	4.43E-05
	(3.54E-05)
Percentage of population 25 years or above with	0.508***
bachelor's degree or higher	(0.166)
Relocation distance	-0.129***
	(0.010)
Urban land area	0.066***
	(0.008)
Center area share	0.338
	(0.238)
Wage	5.02E-07
	(3.29E-06)
Commercial property value	2.89E-03***
	(5.98E-04)
Property tax rate	-0.506
	(0.386)
Distance to highway ramp	0.050***
	(0.016)
Metro and Light Rail station density	0.047
	(0.078)
MARC station density	-0.542**
	(0.275)
Competition within industry	-0.005
	(0.013)
Competition outside industry	-0.174***
	(0.052)
Number of observation	270880
Number of cases	1693
Log likelihood	-5973.2947
Wald χ^2	573.78
LR test for IIA χ^2	37.95

*** Denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are in parentheses. Dissimilarity parameters in all models are smaller than 1. Coefficients of firm-specific variables and dissimilarity parameters are not reported to conserve space.

4.5 Conclusion and Policy Implication

Despite the number of intra-metropolitan relocations greatly exceeds that of inter-metropolitan relocations, they are not of immediate policy interest. A similar situation applies to the relocations of non-headquarter services firms, although they outnumber the relocations of manufacturing firms in both relocation frequency and total scale. The limited attention paid to intra-metropolitan relocations, especially of service firms, could potentially jeopardize local planning practice and development agenda as relocation is a regular way firms adjust their operational strategies. On average, the number of firms and workers involved in relocations is larger than those involved in firm closure each year (VVK 2003). So far, limited checks on the relocation of service firms within a metropolitan area have been provided in the literature.

The study of this essay fills this gap by exploring the relocation pattern of service firms in the Baltimore Metropolitan Region and providing an understanding of locational determinants of firms' intra-metropolitan relocation. The focus of study lies in the impact of agglomeration economies. The results show diversity, specialization, urbanization and localization all have unique positive influences on a firm's relocation decision. No proof was found that supports firms leaving diversity for specialization during relocation. Rather, the evidence suggests a different story from Duranton and Puga's model that diversity could be more important for firms than specialization in searching alternative locations in proximate areas. Duranton and Puga's model states firms relocate to specialized places at the maturity of products. The findings of this essay then suggest the argument might be more appropriate for manufacturing firms but not service firms.

Consistent with findings on firm birth and productivity growth studies, localization presents a more prominent effect than urbanization on firms making relocation choices. The impacts of agglomeration on relocation vary by firms in different age groups and establishment categories. Young firms more value the absolute size of agglomeration, while mature firms benefit more from a larger employment share of their own industry and the diversity of the local economy. Sole proprietorships are found to be less influenced by agglomeration economies as they demand less in labor pooling and matching compared to other standalone firms. Headquarters and branches only favor diversity possibly due to their demands of cross-industry information and ideas. Besides, firms are also attracted to locations with high human capital, adequate land supply, less congestion and better physical environment. Long relocation distance, high wage and intense competition from other industries are the factors that deter firms' entering.

The nested logit model used in this essay tackles the IIA problem of discrete choice model by allowing the correlation between alternatives within a nest but assuming no correlation between alternatives from different nests. However, it is still possible that the impact of locational factor in this essay be overestimated, if a more flexible nested structure was allowed, in which an alternative location can correlate with alternatives in the nest of adjacent locations and with alternatives in the nest of distant locations at the same time (Ibeas et al., 2013). However, evidenced by other studies, the sign and significance level of the estimates should not vary dramatically, especially for agglomeration indicators (Sener et al., 2011; Ibeas et al., 2013). Since agglomeration externalities attenuate rapidly, agglomeration beyond a zip code area should have very limited impact on the relocation choice of firms to that zip code area, and estimation results based on my settings of nesting structures in this essay should still be reliable.

Conventionally, specialization-oriented policies are advocated and adopted by local governments. Contrarily, this essay points to the importance of diversity-oriented policies in sustaining long-run attractiveness to firms. Governments may encourage the concentration of one or a few industries, but they need to maintain a diversified business environment at the same time if the goal is long-term economic prosperous. To achieve this goal, economic and land use policies should allow for more flexibility at the local level.

Chapter 5: Conclusion

This dissertation contributes to the understanding of the agglomeration effect on firm performance and behavior in several aspects. Chapter 2 concludes that localization agglomeration strengthens the negative impact of knowledge spillover on a firm's R&D investment. It also reveals that the negative effect is beneficial to firms by showing a more prominent cost-saving effect than expropriation-avoidance effect on R&D investment reduction. The study suggests localization agglomeration allows firms to acquire a neighboring firms' strategies, ideas and technologies, and then imitate, replicate and sometimes upgrade the knowledge to become their own. This implication lies at the heart of the learning process assumed by Marshall more than a century ago. The exact means by which knowledge spills over is beyond the scope of this dissertation. However, I doubt the spillover of knowledge is deeply embedded in the frequent face-to-face contacts between workers from different firms, the chances of site observation, and the rapid interfirm movement of highly skilled labor.

Previous studies show firms are more innovative in terms of number of patents and inventions they obtained in places with larger localization agglomeration (Jaffe et al.,1993; Deltas and Karkalakos, 2013; Murata et al., 2014; Buzard and Carlino, 2015). To generate those innovative outputs, firms need to either invest in R&D activities or take advantage of other firms' knowledge. As this dissertation identifies a relative low R&D investment for firms in places with a high level of localization agglomeration, it points out a considerable contribution of knowledge spillover in those places leading to a higher level of innovative outputs. This finding emphasizes that knowledge spillover serves as an important channel of knowledge creation and accumulation.

Chapter 2 addresses why firms are more innovative in geographic concentration, while Chapter 3 then connects to the reasons that underlie their higher productivity in dense locations. One of the explanations is that less-productive firms are eliminated from the market. However, agglomeration doesn't only hazard a firm's survival. Firms could survive longer in the presence of a larger share of own industry firms, a more diversified environment and a more intensified concentration. This is consistent with Marshall and Jacobs externalities that emphasize firms' cost saving in transporting labor, intermediate inputs, ideas and products in agglomeration that benefits their operation. In contrast, the absolute scale of concentration presents a negative impact on firm survival. This is consistent with firm selection literature that states denser markets escalate competition and elimination. It reveals that agglomeration encourages entrepreneurship and sharpens it through competition. The overall economy benefits from this kind of improvement in firm efficiency and competence.

The importance of diversity is continuously emphasized in Chapter 4 upon firm intra-metropolitan relocation. Diversity helps sustain the prosperity of one location not only by encouraging firm birth and strengthening firm survival, but also by attracting relocated firms. The finding of Chapter 4 offers a new interpretation of Duranton and Puga's model of the life cycle of product. Relocation is neither the necessary condition nor the sufficient condition upon which a firm changes its location preference. The dynamic advantage of diversified locations may be present whenever firms are in the experimental process for new products and value a more diversified local demand.

The findings of this dissertation provide valuable policy implications for economic development and planning practice. The ultimate goal of economic and planning policy is to let the "invisible hand" work at its best. Land supply and zoning should be directed at more intensely and efficiently connecting firms with each other. Industrial parks and economic clusters are encouraged as they amplify agglomeration economies and accelerate the evolution of the economy at the same time. Policies should also wisely shape the structure of the economy. Although specialization-oriented strategy could lead to rapid growth of a region, a diversified structure ensures a region's long run prosperous. It is hence important for local governments to balance industry specialization and diversity policies.

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