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Industry Growth through Spinoffs and Startups

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Abstract

The literature on industry life cycle suggests that there is some underlying mechanism that generates differences in time for industries reaching their peaks. What causes variation in such peak times across industries? In this paper, I use the Japanese Census of Manufacture and investigate (i) whether creation and destruction of submarkets in an industry affect the length of positive net entry periods and subsequent entry rates, (ii) what type of firm is more likely to be actively engaged in a newly created or destructed submarket, and (iii) how reallocation of unrealized opportunities from incumbent firms to spinoff firms affects the entry process. This study reveals that the creation and destruction of a submarket allow an industry to continue attracting new entrants, that startup and spinoff firms are more likely to enter a newly created submarket than incumbent firms, and that new entry is encouraged when unrealized business opportunities are reallocated smoothly.

Keywords: Industry growth, Product innovation, Industry life cycle, Submarket
JEL classification: O31, O47

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1. Introduction

Some industries continue to grow and attract new entrants for a long period of time and other industries stop doing so within a very short period of time. Klepper (2016), for example, document that it took 15 years or more for the number of firms to reach their peaks in the U.S. tire and automobile industries whereas the number of firms in the penicillin and TV receiver industries reached their peaks very quickly by taking only less than 10 years. The literature on the industry life-cycle has documented a stylized fact that many industries start off with a very few number of firms, but the number of active firms rapidly increases through new entry until a shakeout takes place and, after the shakeout, the industries are typically dominated by a few firms. (Gort and Klepper, 1982; Klepper and Graddy, 1990; Filson, 2001). Since many industries experience this life-cycle pattern, there seems some underlying mechanism that generates differences in the length of periods for an industry reaching its peaks (i.e., shakeout).

What causes such differences across industries? In this paper, I try to answer this question empirically by focusing on a relationship between new entry and the evolution of submarkets (i.e., product innovation process) in a given industry as well as roles of firm heterogeneity played out in product innovation and industry growth. More specifically, I ask a set of the following three questions to investigate a mechanism that encourages or discourages new entry in a given industry. The first question is whether creation and destruction of submarkets in an industry affect the length of positive net entry periods and subsequent entry rates in that industry. The second question asks what type of firms – startup firms, spinoff firms, or incumbent firms – are more likely to be actively engaged in a newly created or destructed submarket. In the third question, I ask how frictions to the pursuit of business opportunities by incumbent firms and frictions to reallocation of unrealized opportunities from incumbent firms to spinoff firms affect entry process at the industry level. Although these three questions seem unrelated to one another, they are actually connected in the following sense. There is anecdotal evidence that spinoff firms tend to pursue a business opportunity their parent firm gave up pursuing and they then create a submarket and compete with their parent firms by providing a new product in the industry where their parent firms currently operate.

The main finding of this study regarding the first question is that the creation and destruction of a submarket allow an industry to continue attracting new entrants so that the timing of a shakeout is delayed. This result is partially consistent with Klepper's (2016) conjecture that an industry continues to attract new entrants when a submarket is created within that industry. In addition to this conjecture, this study reveals the importance of submarket destruction for industry dynamics as well. This study also finds that establishments belonging to startup firms or spinoff firms are more likely to enter a newly created market than establishments belonging to incumbent firms. This indicates that startup firms and spinoff firms are the main player in a new submarket. Regarding the third question, this study shows that new entry is encouraged when unrealized business opportunities are reallocated smoothly to spinoff firms from incumbent firms. This finding can be interpreted as indicating that reallocation of unrealized opportunities from incumbent firms to spinoff firms sparks subsequent entries. The cumulative nature of business and innovation opportunities generates self-enhancing process through which realization of one opportunity becomes a basis for the realization of a next opportunity. In this light, smooth reallocation of unrealized opportunities allows firms to offer new but similar products in an industry (i.e., creation of submarket) and the industry results in continuing to attract new entrants.

The main contribution of this paper is three-fold. Shakeout phenomenon itself has attracted a lot of attention, and several mechanisms that cause a shakeout have been proposed in the industry evolution literature (Jovanovic and MacDonald, 1994; Klepper and Simons, 2000; Barbarino and Jovanovic, 2007), but we have known a very little about why time to reach a peak of the number of active firms differs from industry to industry. This study contributes to this line of research by focusing on product innovation and firm heterogeneity and empirically examining underlying forces for the entry process in industry evolution. The second contribution of this study is to generalize anecdotal evidence and case studies claiming that creation and destruction of products influence a course of industry dynamics (i.e., Schumpeterian industry growth) and that submarket creation is positively associated with a length of industry's prosperity (Geroski 1995; Klepper and Thompson, 2006; Klepper and Golman, 2016). In this study, I use a large-scale data set that contains more than 400 industries to test the generalizability of these claims. This generalization is quite important because it provides sound policy implications for making a fast and persistently growing industry. The third contribution of this study is to provide a new perspective on reallocation effects on industry growth. Most extant studies focus on effects of resource reallocation (Hsieh and Klenow, 2009) or technology reallocation (Collard-Wexler and De Loecker, 2015) on industry and economic growth. This study tries to draw attention to reallocation of unrealized business opportunities and examine its relationship to industry growth. This study reveals that smooth reallocation of unrealized opportunities among different types of firms is positively associated with industry growth in terms of the number of active firms.

The rest of this paper is organized as follows. Section 2 briefly reviews the literatures on industry dynamics, spinoffs, real authority and resource reallocation. Section 3 outlines a theoretical model to guide empirical analysis and interpretation of empirical results. The detailed information of data used in this study is provided in Section 4. Section 5 is devoted to regression analyses regarding submarket creation and destruction, entry and reallocation of unrealized opportunities. Section 6 concludes.

2. Brief Literature Review

This research is related to four strands of the following literatures; Schumpeterian industry growth, submarkets and spinoffs, formal and real authority, and resource reallocation. Since Schumpeter's (1942) work on innovation, economic development and industry dynamics have been examined extensively through a lens of "creative destruction." What we call Schumpeterian growth model was rigorously formalized by Aghion and Howitt (1992) to capture the process of creative destruction in which old firms are replaced by new firms as well as to demonstrate that this process is an important element of economic growth. This Schumpeterian growth model has been also taken to the industry level and helped to improve our understanding of industry dynamics. In particular, the formal model by Klette and Kortum (2004) explicitly incorporates the creation of new goods and the distinction of old goods into an analytical framework and shows that industry dynamics is driven by the process of creative destruction. Their model is quite successful for explaining many stylized facts from firm-level studies about firm growth, entry, exit and size distribution. Lentz and Mortensen (2007) extend the model of Klette and Kortum (2004) to explain a link between growth and firm productivity and effects of reallocation of resources on the aggregate growth. They use Danish data and show that continual reallocation of resources towards new and growing firms through the process of creative destruction accounts for three quarters of the growth in the modeled economy. Regarding the relationship between new market creation and industry growth, Tang (2016) observes that the Japanese manufacturing sector grew through the appearance of new sectors during the period through 1868 to1912.

We can observe a substantial amount of variation in heterogeneity of firm activity within an industry if one defines the industry by the SIC code. By drawing attention to this heterogeneity, Klepper and Thompson (2006) propose that an industry consists of various “submarkets” and argue that regularities about firm growth, entry and exist can be explained well if we take the creation and destruction process of submarkets into account. They take their theoretical predictions to the data about US laser industry where several types of lasers were produced between 1961 and 1994. They found supporting evidence such as that the number of lasers produced by all firms increase with age and that the probability of exit is a decreasing function of the number of lasers produced. In relation to these submarket phenomena, Klepper and Sleeper (2004) present the evidence that spinoff firms and spinout firms tend to produce similar types of products as their parent firms and they therefore paly an important role in the creation of submarkets.

One may argue that spinoff firms are heavily influenced or actually controlled by their former parent firms in spite of the fact that they are a legally independent entity. In particular, this argument appears to fit to Japanese firms better than firms in western countries. Based on the concept of formal and real authority proposed by Aghion and Tirole (1997), Itoh and Hayashida

(1997) theoretically demonstrate that the problem of over-intervention can be mitigated and efficient outcomes about human capital investments can be achieved when authority is delegated to spinoff firms from parent firms. Otsubo (2005) uses a sample of 300 large Japanese firms in the Japanese Company Handbook presents the indirect evidence that the main function of spinoff in cases of Japanese firms is to give workers incentives to make relation-specific investments.

It has been widely recognized that resource allocation is an important channel for industry dynamics through which firm's entry, exit and productivity are influenced significantly. Hseih and Klenow (2009) discuss that distortions in resource allocation are largely responsible for a low level of productivity and show that the aggregate productivity of China and India would increase by about 30 to 50 percent in China and 40 to 60 percent in India if their resources were reallocated to the efficiency level of the United States. Since their seminal work, similar findings about misallocation have been reported by using different data sets around the world. Rather than resource allocation itself, Collard-Wexler and De Loecker (2015) focus on the allocation of technologies as a source of productivity growth. They point to the importance of allocation of technology by showing that the replacement of old production technology by new technology explains the half of the aggregate productivity growth in the US steel industry and that resources are allocated to more productivity firms during the period of technical changes.

3. Conceptual Framework

In this section, a conceptual framework is presented to serve as guiding empirical analyses in Section 5. I extend the industry growth model of Klette and Kortum (2004) and that of Lentz and

Mortensen (2007) by incorporating firm heterogeneity and frictions to innovation opportunities into the analytical framework.

3. 1. Demand and Prices

Time flows continuously and inter-temporal utility of the representative household at time *t* is given by

$$U_t = \int_t^{\infty} e^{-r(s-t)} lnC_t \, ds$$

where C_t is the amount of aggregate consumption, and r is the interest rate. There are different products and the aggregate consumption is given by the CES function:

$$C_t = \left[\int_0^1 \left(A_t(j)x_t(j)\right)^{\frac{\sigma-1}{\sigma}} dj\right]^{\frac{\sigma}{\sigma-1}}$$

where $x_t(j)$ is the quantity of differentiated good *j* at time *t* and $A_t(j)$ is the quality of differentiated good *j* at time *t*. The quality $A_t(j)$ depends on the number of successful innovations in the past $J_t(j)$ and the size of improvement q:

$$A_t(j) = J_t(j)q$$

The profit maximization condition for the final good producer implies

$$P_t(j)A_t(j)x_t(j) = \left(\frac{P_t}{P_t(j)}\right)^{\sigma-1} Z \qquad (1)$$

where $P_t(j)$ is the price of differentiated good *j* without adjusting the quality $A_t(j)$, P_t is the price of final good, and Z is the expenditure of the final good. It follows from the zero profit condition of the final good producer and equation (1) that

$$P_tC_t = \int_0^1 \left(\frac{P_t}{P_t(j)}\right)^{\sigma-1} P_tC_t \, dj$$

which implies

$$P_t = \left[\int_0^1 P_t(j)^{1-\sigma}\, dj\right]^{\frac{1}{1-\sigma}}$$

Using the formula of quality adjusted price that $p_t(j) = A_t(j)P_t(j)$, we obtain

$$P_t = \left[\int_0^1 \left(\frac{p_t(j)}{A_t(j)}\right)^{1-\sigma} dj\right]^{\frac{1}{1-\sigma}}$$

3. 2. Growth Rates and Innovation

Because of the assumption that $P_t C_t = Z$, we have

$$C_t = \frac{Z}{P_t} = Z\left[\int_0^1 \left(\frac{A_t(j)}{p_t(j)}\right)^{\sigma-1} dj\right]^{\frac{1}{\sigma-1}}$$

We assume that firms in each sector of the differentiated products are involved in a Bertrand competition. As a result, the price charged by each firm is the limit price and its markup is given simply by $\frac{\sigma}{\sigma-1}$. Denoting the probability of a successful innovation by δ, the rate of growth in the aggregate consumption is given by

$$g = \delta\left(\frac{q^{\sigma-1}}{\sigma-1}\right) \qquad (2)$$

3. 3. Incentives for Innovation

Consider an incumbent firm which produces *n* variety of goods and generates profit π from each variety. The incumbent firm has an opportunity to make an R&D investment and create a new variety. The R&D expenditure is given by $C(I, n)$, where I is the R&D intensity and $C(\cdot)$

exhibits constant returns-to-scale. The incumbent firm may not pursue all the innovation opportunities, and they may pursue α of the innovation opportunities.

The Bellman equation for the incumbent firm is given by

$$rV(n) = max_I \left\{\pi n - nc\left(\frac{I}{n}\right) + \alpha[V(n+1) - V(n)] + (1-\alpha)V(n)\right\} \quad (3)$$

where V is the value function of the incumbent firm, and r is the interest rate.

The first order condition and envelope condition imply

$$V(n) = vn$$

and

$$I(n) = \lambda n$$

where λ and v are determined by

$$c'(\lambda) = \alpha v$$

and

$$[r - \alpha\lambda - (1-\alpha)]v = \pi - c(\lambda)$$

It follows from these equations that $\frac{d\lambda}{d\alpha} > 0$ and $\frac{d\lambda}{d\pi} > 0$. Thus, the per-product research intensity λ decreases as incumbent firms miss more innovation opportunities. Also, the per-product profit increases the per-product research intensity λ.

A spinoff firm is assumed to mainly pursue an innovation opportunity the incumbent firm gave up pursuing. In other words, the spinoff firm faces $1-\alpha$ of the innovation opportunities. In addition, there is $(1-\gamma)$ degree of industry-level frictions to reallocation of the innovation opportunities from incumbent firms to spinoff firms. Under the conditions, the Bellman equation for the spinoff firm is given by

$$rV(n) = max_I \left\{\pi n - nc\left(\frac{I}{n}\right) + (1-\alpha)\gamma[V(n+1) - V(n)] + \alpha(1-\gamma)V(n)\right\} \quad (4)$$

where V is the value function of the spinoff firm.

The first order condition and envelope condition yield

$$V(n) = vn$$

and

$$I(n) = \lambda n$$

where λ and v are determined by

$$c'(\lambda) = (1-\alpha)\gamma v$$

and

$$[r - (1-\alpha)\gamma\lambda - \alpha(1-\gamma)]v = \pi - c(\lambda)$$

A startup firm starts its business with one variety. Therefore, the Bellman equation for the startup firm is given by Equation (3) with $n = 1$.

3. 4. Industry Dynamics

Let $M_n(t)$ denote the measure of firms with *n* products in an industry at date *t*. As in Klette and Kortum (2004), $M_n(t)$ changes over time according to

$$\dot{M}_n(t) = (n-1)\alpha\lambda M_{n-1}(t) + (n+1)\delta M_{n+1}(t) - n(\alpha\lambda + \delta)M_n(t)$$

for $n \geq 2$ and

$$\dot{M}_1(t) = \eta + (1-\alpha)\gamma\theta + 2\delta M_2(t) - (\alpha\lambda + \delta)M_1(t)$$

Note that $\delta = \alpha\lambda + (1-\alpha)\gamma\theta + \eta$. When $\lambda > 0$, $\theta > 0$ and $\eta > 0$, we have the steady state mass of the firms as

$$M_n = \frac{(\alpha\lambda)^{n-1}(\eta + (1-\alpha)\gamma\theta)}{n\delta^n} = \frac{\kappa}{n}\left(\frac{1}{1+\kappa}\right)^n$$

where $\kappa = \frac{\eta+(1-\alpha)\gamma\theta}{\alpha\lambda}$. The steady state total mass of firms in a given industry is given by

$$M = \kappa ln\left(\frac{1+\kappa}{\kappa}\right) \tag{5}$$

Equation (5) shows that the total mass of firms depend on (i) incentives to innovate by different types of firms (i.e., η, θ and λ), and (ii) frictions to innovation opportunities (i.e., α and γ). The function κ increases with η and θ and decreases with λ. Since the total mass of firms M is an increasing function of κ, the total mass of firms in an industry is larger when innovation intensities of new entrants and spinoff firms are relatively higher than that of incumbent firms. The function κ decreases with α and increases with γ. Thus, the total mass of firms in an industry is larger when incumbents miss innovation opportunities at many times so that spinoff firms can utilize these opportunities to start a new business. Further, the total mass of firms in an industry is larger when spinoff firms face a lesser degree of frictions (i.e., larger value of γ) to start a new business. In the reality, these frictions may include a non-competing clause, regulations, taxes and so forth.

We can also examine the evolution of the number of firms in an industry. Note that

$$M_n(t) \cong \frac{\kappa}{n}[m(t)]^n$$

where

$$m(t) = \frac{\alpha\lambda}{\delta}\left[\frac{\delta - \delta e^{-((1-\alpha)\gamma\theta+\eta)t}}{\delta - \lambda e^{-((1-\alpha)\gamma\theta+\eta)t}}\right]$$

Therefore,

$$M(t) = \sum_{n=1}^{\infty} M_n(t) = \kappa ln\left(\frac{1}{1-m(t)}\right) \qquad (6)$$

Equation (6) implies that

$$\dot{M}(t) = -\kappa\big(1 - m(t)\big)\dot{m}(t)$$

It can be verified that $\dot{M}(t)$ increases with γ and decreases with α. Thus, the number of firms in an industry increases over time more as γ increases or as α decreases.

The rate of convergence or time to reach a steady state depends on the relative magnitude of δ and λ because

$$\frac{\dot{m}(t)}{m(t)} = \left\{\frac{\delta\big((1-\alpha)\gamma\theta+\eta\big)}{\delta-\delta e^{-((1-\alpha)\gamma\theta+\eta)t}} - \frac{\lambda\big((1-\alpha)\gamma\theta+\eta\big)}{\delta-\lambda e^{-((1-\alpha)\gamma\theta+\eta)t}}\right\} e^{-((1-\alpha)\gamma\theta+\eta)t}$$

Since $\delta = \alpha\lambda + (1-\alpha)\gamma\theta + \eta$, the convergence speed depends on frictions α and γ too.

4. Data

The main data in this study come from the Japanese Census of Manufacture (Kogyo-Tokei) between 1980 and 2013, supplemented with 2012 Economic Census for Business Activity.[1] The Ministry of Economy, Industry and Trade has been gathering information about Japanese establishments in the manufacturing sector every year. All establishments with four employees or more located in Japan are subject to the Census of Manufacture, and they are required by law to answer survey questions. The Census of Manufacture contain various pieces of information about establishments such as name, location, the number of employees, value of shipment, wage payment, fixed capital, and so forth.

For this study, product information is the most important piece of information from the Census of Manufacture. Each establishment is required to report a name of each product and a value of each product it produced and shipped every year. Products in the Census of Manufacture are classified into the six-digit level and the number of products at the six-digit level ranges from about 2,200 to 2,300 categories over the period covered by this study. These six-digit level products can be aggregated to the four-digit level, and there are about 450 to 550 products at the four-digit level.[2] For example, processed milk, milk beverage, butter, chees and ice cream are a different

1 The year 2012 is an Economic Census year, and the Census of Manufacture was conducted as a part of the 2012 Economic Census for Business Activity.

2 See the http://www.meti.go.jp/english/statistics/tyo/kougyo/index.html for the details of product classification.

product at the six-digit level, but all of them are classified into dairy products at the four-digit level.

In this study, an industry or a market is empirically defined at the four-digit level, and a submarket is empirically defined at the six-digit level. By using these definitions, we empirically identify the creation and destruction of a submarket in an industry, and investigate how the creation and destruction of a submarket affect industry growth. A basic rationale for these definitions is that many aspects of businesses such as production technology and knowhow and sales and distribution systems are similar within such an industry to a larger extent than across such industries. One can argue that these definitions would not be satisfactory ones because more disaggregated information about products are available for some industries. The main purpose of this study, however, is to examine whether some general pattern of industry growth emerges from a large data set containing a number of industries. Therefore, some specific aspects of products and industries are sacrificed in return for pursuing generalizability.

We also utilize data from the Basic Survey of Japanese Business Structures and Activities (BSJBSA or Kitatsu, hereafter) to identify types of establishments empirically. This survey is conducted by the Ministry of Economy, Industry and Trade every year, and collects information from firms with at least 50 employees and 30 million yen paid-up capital. A particular importance of this data set for the purpose of this study is to contain information about when and how firms were established. In particular, firms answered whether they were established as a new firm or a spinoff firm.

Firms in both the Census of Manufactures and the BSJBSA can be matched through name, telephone number, and postal code matching. Once this matching is complete, a firm type can be assigned to a firm, indicating whether it is a new firm, a spinoff firm or an incumbent firm in a given year. Using the information in the Census of Manufacture about which firm owns which establishment, establishments are classified to a new establishment, a spinoff establishment and an incumbent establishment. One caveat of this matching procedure is that we can identify a type of an establishment in the Census of Manufacture only if a firm that owns the establishment grew large enough to be sampled in the BSJBSA. Some caution should be exercised when interpreting empirical analyses about firm types.

5. Empirical Results

5. 1. Relationship between Submarket Creation and Positive Net Entry

I begin a regression analysis by examining how submarket creation and destruction affect a positive net entry of establishments. In doing so, first, the Japanese manufacturing census data are divided into two periods; (i) 1980 to 1985 and (ii) 1986 to 2013.[3] Then, I empirically ask how submarket creation and destruction between1980 and 1985 affect the length of positive entry period between1986 and 2013.

A unit of analysis in this regression is an industry defined by the four-digit level product category. Submarket creation is identified in the data by the creation of a new product at a six-digit level category. This way of identifying submarket creation is unsatisfactory because there is a gap in time between an actual submarket creation and statistical agency’s recognition of a submarket

3 I tried several ways of dividing periods and got qualitatively the same results.

creation.[4] Nonetheless, this gap will not be critical since this study focuses on a period of rapid entry in the industry life-cycle. A submarket is identified to be destructed when no single establishment produces the product of the submarket any longer or the submarket disappears from the product classification.

A basic estimating equation of this regression analysis is given by

$$y_i = \beta_0 + \beta_1 Creation_i + \beta_2 Destruction_i + \beta_3 Creation_i \times Destruction_i + \beta_4 x_i + \varepsilon_i$$

where y is the maximum periods of consecutive positive entry between 1986 and 2013, $Creation$ is a dummy variable that takes 1 when at least one submarket in industry i is created between 1980 and 1985. The control variables x includes total value of shipments of an industry, and the number of submarkets within an industry.

Table 1 reports estimations results from OLS and hazard regressions. In the specification (I), industries are classified into three categories; (i) an industry that created at least one submarket, (ii) an industry that destructed at least one submarket, and (iii) an industry that neither created nor destructed any submarket (the base category). According to the estimation result from this specification, the coefficient on the submarket creation dummy is positive and statistically significant at the 5 percent level whereas the coefficient on the submarket destruction dummy is not statistically significant at the conventional significance levels. Although this result indicates that submarket creation is likely to extend the period of positive net entry, this specification masks an important fact about an impact of submarket creation and destruction on industry dynamics. In

4 As a general rule, the statistical agency reviews and modifies the current product classification about every five years and create a new product category when a value of shipment of the product becomes a non-negregible share of an induustry total.

the specification (II), the interaction term of submarket creation and submarket destruction is added so that industries are now classified into four categories; (i) an industry that only created a submarket, (ii) an industry that only destructed a submarket, (iii) an industry that both created and destructed a submarket, and (iv) an industry that neither created nor destructed a submarket (the base category).

The OLS estimation result from the specification II shows that, while the coefficient on the market creation dummy is not statistically significant, the coefficient on the interaction term is positive and statistically significant at the 10 percent significance level. The estimation result suggests that the length of positive net entry becomes longer, relative to the base category, by about two years when an industry both created and destructed a submarket. A hazard regression is also conducted to address the truncation issue. The specifications (III) and (IV) present qualitatively the same results as the OLS results. Since the hazard ratio of submarket creation and destructions is less than the unity, a period of positive net entry is less likely to end when an industry both created and destructed a submarket.

[Table 1 is about here]

A similar regression exercise is done by using entry rates as the dependent variable, instead of using the maximum periods of positive entry. Table 2 reports estimation results from this exercise. Specification (I) of Table 2 shows that the average entry rate during the period of 1986 to 2013 becomes higher in the case of submarket creation and destruction than the other cases. We see a similar pattern in the specifications (II) and (IV), though the estimation result in the specification

(III) does not fit into this pattern.

[Table 2 is about here]

Overall, the estimation results in Tables 1 and 2 indicate that establishments are encouraged to enter an industry when that industry both creates and destructs a submarket. This main result can be also interpreted in the context of industry lifecycle. That is, the creation and destruction of a submarket allow an industry to continue to attract new entrants so that the timing of a shakeout is delayed. Thus, an industry tends to grow in terms of the number of establishments when the industry evolves through the creation and destruction of submarkets.

5. 2. Who creates and destructs a submarket?

Since the previous section reveals the importance of submarket creation and destruction, it is worthwhile to investigate what type of establishment is more likely to create or destruct a submarket in a given industry. In particular, it is interesting to examine whether it is an establishment owned by a startup firm, a spinoff firm or an incumbent firm that creates or destructs a submarket. That said, the nature of the Japanese manufacturing census data does not permit us to identify an establishment or a firm that has actually created or destructed a submarket. To see some aspect of industry dynamics through this lens, the empirical question mentioned above is reformulated as a question of what type of establishment is more likely to be engaged in a newly created submarket or in a submarket that is about to be destructed.

Unlike the empirical analysis in the previous section, the first analysis of this section uses an establishment as a unit of analysis and focuses on industries that created or destructed at least one submarket. More specifically, I estimate the probability of being a newly created (destructed) submarket:

$$Pr(D_{it} = 1) = g(\beta_0 + \beta_1 Spinoff_{it} + \beta_2 Startup_{it} + \beta_3 Acquisition_{it} + \beta_4 x_{it})$$

where D_{it} is a dummy variable that takes 1 if establishment *i* is in a newly created market in a given industry at time *t*. The independent variables include establishment types and controls such as total value of shipments, the number of products shipped and industry dummies. The variable $Spinoff_{it}$ is equal to 1 if an establishment is owned by a firm that were legally separated as a spinoff firm from a parent firm within the past five years from year *t*. The variable $Startup_{it}$ is equal to 1 if an establishment belongs to a newly started firm within the window of the past five years from year *t*. The variable $Acquisition_{it}$ is a dummy variable indicating whether an establishment belongs to a firm that was created through acquisition process within the past five years from year *t*. The baseline category is an establishment belonging to a firm operating in an industry for more than 5 years.

Estimation results are presented in Table 3. In the Specification (I), all establishments belonging to new firms are bunched together to see a role of new firms in a newly created submarket. The coefficient on the new firm dummy is positive and statistically significant at the 1 percent significance level. This indicates that establishments belonging to new firms are more likely to enter a newly created submarket than establishments belonging to incumbent firms. In the Specification (II), heterogeneity of new firms are accounted for. According to the estimation result from the specification (II), while the coefficient on the acquisition dummy is not statistically significant, the coefficients on the spinoff dummy and startup dummy are positive and statistically significant at the 10 percent and the 1 percent significance levels, respectively.

Turning our attention to a submarket that is about to be destructed, the estimation results in the specifications (III) and (IV) pose a mirror image of the estimation results about a newly created submarket. Startup firms and spinoff firms are more likely than incumbent firms to avoid a submarket that is going to be destructed whereas acquisition firms are more likely to enter that submarket.

The estimation results in Table 3 imply that firm age (i.e., young firms versus incumbent firms) does not matter so much for active involvement in a newly created submarket or in a destructed submarket, but different types of new firms play different roles in creation and destruction of submarkets of a given industry.

[Table 3 is about here]

Next, I examine a similar issue from a slightly different viewpoint by focusing on the distribution of firm types within an industry. More specifically, I investigate how the probability of submarket creation or destruction in a given industry at time t+1 is affected by the existence of particular firm types at time t. That is, the estimating equation is given by

$$Pr(D_{it+1} = 1) = g(\beta_0 + \beta_1 Spinoff_{it} + \beta_2 Startup_{it} + \beta_3 Acquisition_{it} + \beta_4 x_{it})$$

where D_{it+1} is equal to 1 if industry i creates a newly submarket at time t+1 (or destructed a submarket), and firm types variables take on 1 if each type exists in industry i at time t. Note that a unit of analysis switches back to an industry in this regression analysis.

Table 4 presents estimation results about such probabilities. According to Table 4, we can see that a submarket is more likely to be created or destructed when there are startup firms in an industry, but existence of spinoff firms and acquisition firms have no impact on such probabilities. This appears to suggest that startup firms are critical for submarket creation and destruction, although cautions should be exercised to interpret this result. As mentioned in Section 4, data matching process is far from perfect. In particular, the matching process tends to pick up successful startups and spinoffs and this may lead to a biased result.

[Table 4 is about here]

5. 3. Reallocation of unrealized opportunity with frictions

In this section, I use the model outlined in Section 3 to estimate frictions to pursuit of business opportunities by incumbent firms (i.e., the parameter α) as well as reallocation of unrealized opportunities between incumbent firms and spinoff firms (i.e., the parameter γ). Once the estimates of such frictions are obtained, I empirically examine how these frictions shape an industry dynamics by influencing a net entry rate of the industry.

In section 3, the optimal conditions of an incumbent firm are derived as

$$c'(\lambda) = \alpha v$$

and

$$\pi = [r - \alpha\lambda - (1-\alpha)]v + c(\lambda)$$

To proceed further, I assume that the cost function is quadratic with respect to λ. That is, $c(\lambda) = \phi_0 + \frac{1}{2}\phi_1\lambda^2$. Under this assumption, these two optimal conditions for incumbent firms yield

$$\pi_{incumbent} = \phi_0 + [r - (1-\alpha)]v - \frac{1}{2}\frac{\alpha^2}{\phi_1}v^2 \qquad (7)$$

Equation (7) forms a basis for estimating α. Given the interest rate r, the parameter α can be estimated from the regression of $\pi_{incumbent}$ on v. Similarly, for incumbent firms, we have

$$\pi_{spinoff} = \phi_0 + [r - \alpha(1-\gamma)]v - \frac{1}{2}\frac{\gamma^2(1-\alpha)^2}{\phi_1}v^2 \qquad (8)$$

Equation (8) implies that the parameter γ can be estimated from the regression of $\pi_{spinoff}$ on v once we obtain an estimate of α and r.

Data on (π, v) can be calculated from profit data of each establishment. For this analysis, π is the current profit of an establishment calculated from the Census of Manufacture, and v is a sum of discounted future profits. Since the panel data are only available after 1986, I calculate the average current profits of each establishment between 1986 and 1990 and use this average as the current profit π. Regarding the calculation of v, I use profits of each establishment between 1991 and 2013 as a stream of future profits. Then, π is regressed on v and v^2 separately for a set of incumbent establishments and a set of spinoff establishments in a given industry to estimate α and γ. To calculate α and γ, the interest rate r is set to 0.05.

Table 5 presents the distributions of estimates of α and γ across industries. The mean of estimates of α is about 0.992, and it suggests that there is some friction to the pursuit of business opportunities by incumbent firms. We can also observe that there is some variation in the estimates of α and γ across industries. Such variations are now used to examine to what extent these frictions are critical for variation in the number of net entry across industries.

[Table 5 is about here]

Table 6 shows estimation results about a relationship between frictions and entry rates. According to Table 6, the coefficient on α is negative and is not statistically significant at the conventional significance levels whereas the coefficient on γ is statistically significant at the 5 percent or the 10 percent significance level.

Notice that a larger value of α indicates a lesser degree of friction to the pursuit of business opportunities by incumbent firms. Although the coefficient on α is not statistically significant, the negative sign of the coefficient is in line with the model's prediction. When α is high, incumbent firms realize many business opportunities in a given industry so that there is a little room for startup firm and spinoff firms to enter that industry.

A larger value of γ means a lesser degree of friction to reallocation of unrealized opportunities from incumbent firms to spinoff firms. In other words, spinoff firms can pursue unrealized opportunities of incumbent firms more often as a value of γ becomes larger. The positive sign of the coefficient on γ can be interpreted as indicating that new entry is encouraged when unrealized business opportunities are reallocated smoothly to spinoff firms from incumbent firms. When product innovation is cumulative process in that one innovation becomes a foundation for next innovations (Aghion et al., 2008), subsequent innovations may not come to existence if some frictions do not allow some firms to pursue unrealized innovation opportunities of other firms. In light of this insight, the estimation results in Table 6 seem to imply that this cumulative nature of business and innovation opportunities generates self-enhancing process of new entry in the sense that reallocation of unrealized opportunities from incumbent firms to spinoff firms sparks subsequent entries.

[Table 6 is about here]

6. Conclusion

This study used the large-scale data of the Japanese Census of Manufacture between 1980 and 2013 to empirically investigate the process of Schumpeterian industry growth, its generalizability and the role of reallocation of unrealized opportunities in industry dynamics. The empirical analyses of this study showed that the creation and destruction of products have a positive impact on the length of entry periods and entry rates, that startup firms and spinoff firms are more likely than incumbent firms to be involved in a newly created submarket and that an industry continues to attract new entrants when reallocation of unrealized opportunities among different firm types functions well without serious frictions.

Several caveats need to be recognized in order to interpret the main findings of this study appropriately. First, this study does not intend to establish and claim any causal relationship. All the findings of this study should be interpreted as indicating some association among the research variables of this study. Second, some insights from the empirical analyses of this study rely on indirect evidence as well as strong assumptions about functional forms. For example, the friction parameters were estimated by assuming that the cost function was quadratic with respect to innovation intensity. Some generalization about the functional form needs to be investigated since an alternative specification may change the estimation results qualitatively. Finally, the sample used in the empirical analyses biases towards establishments belonging to successful firms. This bias may affect all types of firms – startup, spinoff and incumbent firms – in the same direction, but it is hard to detect and infer the direction of this bias. Although these caveats raise some concern, this study presented interesting relationships between innovation, firm heterogeneity and industry dynamics.

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Tables

Table 1: Positive Net Entry Periods and Submarkets

	Dependent variable: Positive Entry Periods			
	OLS		Hazard Ratio	
	I	II	III	IV
Submarket Creation	0.7455 **	0.5041	1.364	1.28946
	(0.3685)	(0.3899)	(2.819)	(1.65473)
Submarket Destruction	0.4424	0.1973	1.365	1.27897
	(0.3512)	(0.3744)	(1.909)	(1.79702)
Creation & Destruction		1.9854 *		0.00004 **
		(1.0728)		(0.000031)
Value of Shipments	0.0004 **	0.0004 **	0.997	0.99739
	(0.0002)	(0.0002)	(0.002)	(0.00213)
Number of Products	-0.0966 ***	-0.0853 **	1.247 ***	1.25210 **
	(0.0344)	(0.0349)	(0.127)	(0.12917)
No. of observations	440	440	440	440

Note: ***, **, and * indicate that a coefficient is statistically significant at 1 percent, 5 percent and 10 percent significance levels, respectively.

Table 2: Net Entry Rates and Submarkets

	Dependent variable: Entry Rates			
	I (1986 - 2013)	II (1986 – 1990)	III (1996 – 2000)	IV (2006 – 2010)
Submarket Creation	-0.003440	0.007442 *	0.0096742	0.000221
	(0.006166)	(0.004039)	(0.0061287)	(0.007510)
Submarket Destruction	-0.000089	-0.002062	-0.0027783	0.003000
	(0.005966)	(0.003908)	(0.0059305)	(0.007267)
Creation & Destruction	0.030530 *	0.027452 **	0.0136738	0.045175 **
	(0.017152)	(0.011236)	(0.0170497)	(0.020892)
Value of Shipments	0.000003	0.000003	2.50E-06	0.000003
	(0.000003)	(0.000002)	(0.000002)	(0.000003)
Number of Products	-0.001473 ***	-0.000961 ***	-0.0017621 ***	-0.000525
	(0.000548)	(0.000359)	(0.0005445)	(0.000667)
No. of observations	440	440	440	440

Note: ***, **, and * indicate that a coefficient is statistically significant at 1 percent, 5 percent and 10 percent significance levels, respectively.

Table 3: Net Entry Rates and Submarkets

Logit model Marginal effects	In Newly Created Submarket		In Newly Destructed Submarket	
	I	II	III	IV
New firm dummy	0.0249 ***		-0.0182 ***	
	(0.0051)		(0.0048)	
Spinoff dummy		0.0260 *		-0.0279 *
		(0.0155)		(0.0159)
Acquisition dummy		0.0036		0.0445 ***
		(0.0151)		(0.0095)
Startup dummy		0.0280 ***		-0.0357 ***
		(0.0057)		(0.0060)
Observations	672,543	672,543	823,060	823,060
Year Dummy	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate that a coefficient is statistically significant at 1 percent, 5 percent and 10 percent significance levels, respectively.

Table 4: Firm Types. Submarket Creation and Destruction

Mlogit model Marginal effects	I Creation		II Destruction	
Spinoff dummy	-0.0013		0.0235	
	(0.0190)		(0.0207)	
Acquisition dummy	0.0223		0.0117	
	(0.0182)		(0.0205)	
Startup dummy	0.0674	***	-0.0616	***
	(0.0220)		(0.0201)	
Observations	1,481		1,481	
Year Dummy	Yes		Yes	
Controls	Yes		Yes	

Note: ***, **, and * indicate that a coefficient is statistically significant at 1 percent, 5 percent and 10 percent significance levels, respectively.

Table 5: Estimation of Friction Parameters α and γ

	Mean	Std. Dev.	10th	25th	50th	75th	90th
alpha	0.9916	0.0288	0.9599	0.9744	0.9887	1.0044	1.0303
gamma	1.0383	0.2081	0.9279	0.9514	0.9979	1.0637	1.1540

Note: ***, **, and * indicate that a coefficient is statistically significant at 1 percent, 5 percent and 10 percent significance levels, respectively.

Table 6: Entry Rates and Frictions

	Dependent variable: Entry Rates			
	I (1991 – 2013)	II (1991 – 1995)	III (1996 – 2000)	IV (2001 – 2005)
alpha	-0.0648	-0.2025	-0.1050	-0.2052
	(0.1133)	(0.1373)	(0.0868)	(0.2272)
gamma	0.0114 **	0.0172 **	0.0260 ***	0.0260 ***
	(0.0050)	(0.0078)	(0.0054)	(0.0083)
No. of observations	97	97	97	97

Note: ***, **, and * indicate that a coefficient is statistically significant at 1 percent, 5 percent and 10 percent significance levels, respectively.