Product Switch and Customer Acquisition: Evidence from Japanese Firms

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Product Switch and Customer Acquisition: Evidence from Japanese Firms*

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Abstract

Resource reallocation within firms drives economic growth in a manner similar to inter-firm reallocations from unproductive to productive sectors. Such within-firm reallocation is exemplified by struggling firms that develop new core businesses and achieve significant growth, as often highlighted in real-world business cases. Using panel data on Japanese firms, we document these within-firm reallocations by identifying top-selling product switches to new products. We provide evidence that firms undergoing a major business switch exhibit sales and productivity growth. These firms also show distinctive customer acquisition behavior before and after the switch. Since the customer base that fits a firm's existing business may not appreciate its new business, the switching firm rationally delays the switch until a sufficient number of new potential customers is acquired. We present a model of frictional markets where sellers and buyers are matched and explain the patterns of customer acquisition and search efforts we found in the data.

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1 Introduction

Resource reallocation from unproductive firms or industries to productive ones drives economic growth through creative destruction. Workers often bear the brunt of this process in the frictional job creation and destruction cycle. Alternatively, firms can achieve resource reallocation by restructuring their businesses from unproductive sectors or products to more productive ones. Within-firm reallocations are important to economic growth policy debates, as they may alleviate the frictional aspects of creative destruction and enhance workers' welfare. This paper documents firms that adapt to changing environments by switching their main products.

Business cases highlight the significant restructuring of main products as success stories in a real-world narrative for a large firm experiencing technological change. For example, Fujifilm, one of the most prominent manufacturers of photography film, faced a disruption in demand for photography film due to the rise of digital cameras in the 2000s. The company transitioned its main business to materials, healthcare, and biotechnology by leveraging the core technology developed in film production. Fujifilm's success in product transition contrasts with Eastman Kodak, the photography film giant, which filed for bankruptcy in 2012, the "Kodak moment" of creative destruction (Ho and Chen 2018, The Economist 2012). Another example is IBM, once a prominent producer of hardware devices such as HDDs and PCs. When its products became obsolete due to breakthroughs by competing manufacturers, it shifted its main business to consulting, business infrastructure, and software, which require advanced knowledge (Urso et al. 2012).

Finding new customers is a significant challenge when a firm innovates and renews its production system. Before switching its main product, a firm needs to ensure that a solid clientele exists for the new product in the future. Faced with difficulties locating potential customers, a firm with an opportunity to switch to a new product undertakes customer search activities. Since the search process takes time, the firm is expected to begin the search before the product switch and postpone the launch until it gathers a sufficient number of potential customers. We present a model based on Eaton et al. (2022) to formulate the firm's search behavior before a product switch.

The paper's main contribution is providing empirical findings that support the model's implications and document the significant impacts of product switches on firm growth. To empirically identify product switches in our dataset, we focus on the incidents when a firm's top-selling product is replaced by a new product that the firm did not produce in the previous period. We will henceforth refer to this top-selling product switch as "TPS." TPS signifies a change in a firm's main product regarding sales. As such, TPS implies a drastic transformation in a firm's production structure since the new main product was not part of the previous product mix. Indeed, earlier studies on product mix (Bernard et al. 2010, 2011) report that half of U.S. manufacturing firms change their product mix over 10 years. In contrast, the annual rate of TPS in our sample is less than 1%, as we will detail in the empirical section. The rare occurrences of TPS compared to common changes in product mix suggest that TPS necessitates a significant transformation in a production system and a crucial managerial decision.

We focus on switching to a product the firm did not produce in the last period to highlight its managerial decisions. Product sales ranks within a firm can fluctuate due to unexpected random shocks. Moreover, to add a new product, management needs to find new customers who evaluate the products differently from existing customers. Our definition of TPS represents a radical reform of a firm's production and aligns better with the model that emphasizes the firm's preparation for the product switch.

We utilize the dataset from Tokyo Shoko Research, Ltd., a Japanese credit research company. In addition to standard firm-level information and financial statements typical of panel datasets, this dataset includes detailed records on firms' product mixes and inter-firm transaction relationships. Furthermore, we analyze the marketing and entertainment expenditure data from financial statements to trace the TPS firms' search efforts to find customers. These data enable us to empirically examine the impact of TPS on firms' customer acquisition strategies.

Related literature This research is related to three strands of literature. The first strand of literature to which this study belongs concerns the product switch behavior of multi-product firms (Bernard et al. 2003, 2010, 2011, Broda and Weinstein 2010, Goldberg et al. 2010, Kawakami and Miyagawa 2013, Mayer et al. 2014, Timoshenko 2015). This literature examines how multi-product firms modify their product portfolios or product mixes by adding and discontinuing products. Bernard et al. (2010) presents fundamental empirical facts on product switching among U.S. manufacturing firms. Kawakami and Miyagawa (2013), using the Japanese manufacturing firm dataset (Census of Manufacture), conducts a similar analysis to Bernard et al. (2010) and reports that

Japanese firms engage in product switching less frequently than their U.S. counterparts. While these studies broadly analyze product additions and discontinuations without focusing on product ranking within a firm's product mix, they do not specifically address the switching of top-selling products, our primary focus.

The strand of literature most closely related to our study concerns firms' switching of core products, primary sectors, or main industries (Bernard et al. 2006, Kuosmanen et al. 2022, Pandey et al. 2020, Ding et al. 2022, Bernard and Jensen 2004, Greenaway et al. 2008, Kuosmanen and Kuosmanen 2024, Elliott et al. 2019, Newman et al. 2013). This body of research reports that external factors such as increased import competition (Bernard et al. 2006, Ding et al. 2022, Greenaway et al. 2008) or rising electricity prices (Elliott et al. 2019) lead to a greater incidence of firms shifting their core products or industries to the more adequate ones in terms of the efficiency of the entire economy. However, these studies primarily concern aggregate trends and do not track individual firms' behavior and performance over time. Our paper addresses this gap by unveiling firm-level dynamics.

The final strand of literature relevant to this study pertains to demand acquisition (Foster et al. 2008, 2016, Alfaro-Urena et al. 2022). A pioneering study in this field is Foster et al. (2008), which empirically highlights the importance of demand-side factors in explaining firm-level productivity heterogeneity. While entrants may have a quantitative productivity advantage over incumbents, they often suffer from demand-side disadvantages, leading to relatively lower revenue-based productivity. Firms that switch to a new top-selling product can be considered entrants in that particular product market. By incorporating frictional customer acquisition into the framework, our study provides insights into how firms engaging in TPS navigate demand-side disadvantages associated with product market entry.

The remainder of this paper is structured as follows. Section 2 presents a dynamic model of firms considering TPS and motivates our empirical study concerning customer acquisition. Section 3 shows a numerical example of the model introduced in Section 2 and verifies the model implications. Section 4 outlines our empirical strategy to capture the timeline of firm behavior. Section 5 details the data we use. Section 6 presents our main empirical findings. Section 7 concludes.

2 A model of product switch and customer acquisition

We consider the problem of a seller firm operating in a frictional market for customer acquisition. The firm aims to maximize its profits while acquiring potential buyers. Potential buyers are firms eligible to initiate transactions at any time but are not necessarily engaged in actual transactions. At each moment, the seller firm selects buyers from its potential customer base to establish an actual customer base, from which it generates profits.

The acquisition of potential customers occurs in a frictional market, where seller and buyer firms are matched stochastically. Seller firms can increase their likelihood of finding potential customers by incurring a search effort cost. We focus on the customer acquisition behavior of firms facing such a market, analyzing how they optimize their strategies to maximize profits.

2.1 Profit structure

There are J types of buyer firms. Let p_j for $j = 1, 2, \ldots, J$ denote the number of type-j buyers a given seller firm has in its potential customer base. A vector $\boldsymbol{p} = (p_1, \ldots, p_J)$ expresses the seller firm's potential customer base. The actual customer base is denoted by $\boldsymbol{b} = (b_1, \ldots, b_J)$. Then, $\boldsymbol{b}$ is determined by the profit maximization problem for each period, satisfying $b_j \leq p_j$ for all $j \in J$. An instantaneous maximized profit function given $\boldsymbol{p}$ is $\pi^R(\boldsymbol{b}; \boldsymbol{p})$, where the superscript R indicates a production system R, as defined shortly.

The actual customer base $\boldsymbol{b}$ is determined in the seller's maximization behavior that generates $\pi^R(\boldsymbol{b}; \boldsymbol{p})$. The profit earned by a seller with the production system R through its sales to a buyer of type-j is specified as

$$r_j^R = (J - j + 1)/J. \tag{1}$$

Thus, the seller's profitability varies with the buyer type. Type-1 buyer firm yields the largest profit to a seller, while type-J yields the smallest profit for a seller firm. Provided with the profitability from each buyer, the instantaneous profit function $\pi^R(\boldsymbol{b}; \boldsymbol{p})$ is determined as

$$\pi^R(\boldsymbol{b}; \boldsymbol{p}) = \max_{\boldsymbol{b} \leq \boldsymbol{p}} \sum_{j=1}^{J} b_j r_j^R - c(n_b)^{\eta_R}, \tag{2}$$

where $\eta_R > 1$, $n_b := \sum_{j=1}^{J} b_j$, and $\boldsymbol{b} \leq \boldsymbol{p}$ denotes $b_j \leq p_j$ for all j. The first term in the right-hand side of (2) represents the total profit obtained by a seller firm. The second term is the cost of retaining a business partnership with buyers, where c is the normalizing constant parameter and n_b is the total number of actual buyers. The exponent parameter $\eta_R > 1$ implies an increasing marginal cost of holding more actual buyers.

The customer base $\boldsymbol{b}$ is determined as follows. Since the type-1 buyer is the best fit for R according to (1), the seller firm starts trading with type-1 and other types in ascending order up to type-J among its potential buyer base $\boldsymbol{p}$ as far as the cost for holding the partnership $c(n_b)^{\eta_R}$ permits. By so doing, the actual buyer base and the instantaneous profit are determined through the profit maximization problem above, given the potential buyer base $\boldsymbol{p}$.

2.2 Search and matching

The potential buyer base $\boldsymbol{p}$ is a state variable accumulated through the search behavior of a seller firm. We specify the market structure following Eaton et al. (2022). Consider a two-sided market with a continuum of seller and buyer firms. For simplicity, we assume that a customer firm can have at most one seller firm as its supplier, while a seller can have multiple buyers as its potential customers.

A seller firm can be in one of three states: $i \in \Omega = \{RR, RN, NN\}$. A seller in state RR has a production system R only. A seller is in state RN if it has innovated a new production system N, as defined later, but operates in an old production system R. Finally, a seller is in state NN if it has innovated and switched to the new production system N.

M_j^B denotes the measure of buyers with type-j, and $M_i^S(\boldsymbol{p})$ is the measure of sellers in state i with a potential customer base $\boldsymbol{p}$. Sellers in i with customer base $\boldsymbol{p}$ decide search effort $\sigma_i(\boldsymbol{p})$, which helps the seller to be matched with buyers. The "visibility" of each side is defined following Eaton et al. (2022),

$$H^B = \sum_j M_j^B,$$

$$H^S = \sum_{i\in\Omega} \sum_{\boldsymbol{p}\in\boldsymbol{P}} \sigma_i(\boldsymbol{p}) M_i^S(\boldsymbol{p}),$$

where $\boldsymbol{P}$ is the set of all possible $\boldsymbol{p}$.

A matching function maps the visibility (H^B, H^S) to the total measure of matches X as

$$X = H^S(1 - \exp(-H^B/H^S)). \tag{3}$$

With this matching technology, we define the seller's market slackness θ as follows.

$$\theta := X/H^S \tag{4}$$

In addition, the share of matches involving buyers of type-j, v_j^B is written as

$$v_j^B = M_j^B/H^B, \tag{5}$$

because the probability that a unit measure of buyers of type-j matches that of sellers is equal across j.

2.3 Seller's problem

We adopt a simple version of a firm's optimization problem in Eaton et al. (2022) and add the structure of selecting an actual customer base from the potential customer base. The problem of a seller firm having only a production system R in the setting of continuous time is expressed by the following HJB equation:

$$\rho V_{RR}(\boldsymbol{p}) = \max_{\sigma_{RR}} \pi^R(\boldsymbol{b};\boldsymbol{p}) - k(\sigma_{RR}(\boldsymbol{p})) + \begin{bmatrix} \sigma_{RR}(\boldsymbol{p})\theta \sum_j v_j^B(V_{RR}(\boldsymbol{p}+\mathbf{1}_j) - V_{RR}(\boldsymbol{p})) \\ +\delta \sum_j p_j(V_{RR}(\boldsymbol{p}-\mathbf{1}_j) - V_{RR}(\boldsymbol{p})) \end{bmatrix}, \tag{6}$$

where ρ and δ denote an instantaneous discount factor and a separation rate, respectively, and $k(\sigma_i(\boldsymbol{p}))$ denotes search cost. The terms in the square bracket indicate the gain and loss of the values involving the stochastic variation of a state variable $\boldsymbol{p}$, the potential customer base, where $\mathbf{1}_j$ denotes a vector of length J that has one in the j-th element and zeros in all the others. Thus, the first term in the square bracket in (6) represents the addition of potential buyers, and the second represents the loss.

The search cost $k(\sigma_i(\boldsymbol{p}))$ incurred by a seller firm depends on the search effort $\sigma_i(\boldsymbol{p})$ exercised by the firm. Specifically, the search cost is a quadratic function of the search effort,

$$k(\sigma_i(\boldsymbol{p})) = k_0\{\sigma_i(\boldsymbol{p})\}^2/(n_p+1)^\gamma, \tag{7}$$

where $n_p := \sum_{j=1}^J p_j$ is the number of potential customers and k_0 is a normalizing parameter. The search cost may be increasing or decreasing in the number of potential buyers n_p, depending on the parameter γ.

A seller firm chooses a search effort policy $\sigma_{RR}(\boldsymbol{p})$. As the seller firm increases its search effort, the seller's search effort costs rise quadratically in σ_{RR}, whereas the expected return increases linearly via the matching probability in the first term of the square bracket. The tradeoff pins down the optimal policy as in Eaton et al. (2022),

$$\frac{\partial k(\sigma_{RR}(\boldsymbol{p}))}{\partial \sigma_{RR}(\boldsymbol{p})} = \theta \sum_{j=1}^{J} v_j^B (V_{RR}(\boldsymbol{p} + \mathbf{1}_j) - V_{RR}(\boldsymbol{p})). \tag{8}$$

2.4 Switch of a production system

In the previous subsection, we considered a seller firm having only a production system R. We postulate that some seller firms with a production system R innovate a new production system N. A firm must adopt either of the two production systems R or N; it cannot adopt both. We also assume that once the firm switches the production system from R to N, it cannot return to N. We denote the state RN in which a firm innovated a new production method but has not adopted it yet. We examine a firm's switching process from R to N.

When the new production system N is adopted by a seller, compatible types of buyer firms differ from those under the previous production system R. Specifically, the individual profit earned from a buyer firm of type-j is given by

$$r_j^N = j/J. \tag{9}$$

Under N, the most compatible buyer is type-J, and the worst match is type-1, which is the opposite under R.

We further assume that adopting N reduces the cost of retaining a buyer. The instantaneous profit function $\pi^N(\boldsymbol{b}; \boldsymbol{p})$ is specified as

$$\pi^N(\boldsymbol{b}; \boldsymbol{p}) = \max_{\boldsymbol{b} \leq \boldsymbol{p}} \sum_{j=1}^{J} b_j r_j^N - c(n_b)^{\eta_N} \tag{10}$$

where a new parameter η_N satisfying $1 < \eta_N < \eta_R$. We will discuss whether this assumption is compatible with the empirical facts we present in the empirical part.

Due to the reduced customer holding costs under N, a seller can generate higher instantaneous profits from a larger number of compatible customers. However, when an innovation arrives, the seller lacks a sufficient potential customer base because they operated under R and were not incentivized to maintain a large customer base. Since acquiring potential customers takes time, the firm wants to avoid short-term low profits until a sufficient number of compatible customers are found.

The following HJB equations define the dynamic problem of a firm that has innovated:

$$\rho V_{RN}(\boldsymbol{p}) = \max_{\sigma_{RN},x} \pi^R(\boldsymbol{b};\boldsymbol{p}) - k(\sigma_{RN}(\boldsymbol{p})) + (1-x)\left[\begin{array}{l} \sigma_{RN}(\boldsymbol{p})\theta \sum_j v_j^B(V_{RN}(\boldsymbol{p}+\mathbf{1}_j) - V_{RN}(\boldsymbol{p})) \\ +\delta \sum_j p_j(V_{RN}(\boldsymbol{p}-\mathbf{1}_j) - V_{RN}(\boldsymbol{p})) \end{array}\right]$$
$$+ x(V_{NN}(\boldsymbol{p}) - V_{RN}(\boldsymbol{p})), \tag{11}$$

$$\rho V_{NN}(\boldsymbol{p}) = \max_{\sigma_{NN}} \pi^N(\boldsymbol{b};\boldsymbol{p}) - k(\sigma_{NN}(\boldsymbol{p})) + \left[\begin{array}{l} \sigma_{NN}(\boldsymbol{p})\theta \sum_j v_j^B(V_{NN}(\boldsymbol{p}+\mathbf{1}_j) - V_{NN}(\boldsymbol{p})) \\ +\delta \sum_j p_j(V_{NN}(\boldsymbol{p}-\mathbf{1}_j) - V_{NN}(\boldsymbol{p})) \end{array}\right]. \tag{12}$$

The value function has an additional state from $\{RN, NN\}$. $V_{RN}(\boldsymbol{p})$ denotes the value of staying with R, whereas $V_{NN}(\boldsymbol{p})$ is the value of adopting N. Adoption policy is denoted by $x \in \{0, 1\}$, which takes 1 when a seller switches from R to N and takes 0 otherwise.

2.5 Measures

The law of motion for the measure of firms in RR with potential buyers $\boldsymbol{p}$ is given by

$$\dot{M}_{RR}^S(\boldsymbol{p}) = \sum_j \sigma_{RR}(\boldsymbol{p}-\mathbf{1}_j)\theta v_j M_{RR}^S(\boldsymbol{p}-\mathbf{1}_j) + \delta \sum_j (p_j+1) M_{RR}^S(\boldsymbol{p}+\mathbf{1}_j)$$
$$- \left[\sigma_{RR}(\boldsymbol{p})\theta M_{RR}^S(\boldsymbol{p}) + \delta n_p M_{RR}^S(\boldsymbol{p})\right], \tag{13}$$

where the first and second terms represent inflows of firms due to the addition and separation of potential customers from other measures. The third term indicates outflows due to the addition and separation of customers.

Similarly, the laws of motion for the measures of firms in RN and NN with potential buyer $\boldsymbol{p}$

are given by

$$
\begin{aligned}
\dot{M}^S_{RN}(\boldsymbol{p}) =& \sum_j (1 - x(\boldsymbol{p} - \mathbf{1}_j))\sigma_{RN}(\boldsymbol{p} - \mathbf{1}_j)\theta v_j M^S_{RN}(\boldsymbol{p} - \mathbf{1}_j) + \delta \sum_j (1 - x(\boldsymbol{p} + \mathbf{1}_j))(p_j + 1) M^S_{RN}(\boldsymbol{p} + \mathbf{1}_j) \\
&- (1 - x(\boldsymbol{p})) \left[\sigma_{RN}(\boldsymbol{p})\theta M^S_{RN}(\boldsymbol{p}) + \delta n_p M^S_{RN}(\boldsymbol{p})\right] \\
&- x(\boldsymbol{p}) M^S_{RN}(\boldsymbol{p}), \qquad (14) \\
\dot{M}^S_{NN}(\boldsymbol{p}) =& \sum_j \sigma_{NN}(\boldsymbol{p} - \mathbf{1}_j)\theta v_j M^S_{NN}(\boldsymbol{p} - \mathbf{1}_j) + \delta \sum_j (p_j + 1) M^S_{NN}(\boldsymbol{p} + \mathbf{1}_j) \\
&- \left[\sigma_{NN}(\boldsymbol{p})\theta M^S_{NN}(\boldsymbol{p}) + \delta n_p M^S_{NN}(\boldsymbol{p})\right] \\
&+ x(\boldsymbol{p}) M^S_{RN}(\boldsymbol{p}). \qquad (15)
\end{aligned}
$$

The last terms in the right-hand side of the law of motion of M^S_{RN} and M^S_{NN} represent the outflow and inflow due to the switch of production system from R to N.

The sum of each measure is exogeneously given by $M^S_{pre} = \sum_{\boldsymbol{p} \in \boldsymbol{P}} M^S_{RR}(\boldsymbol{p})$ and $M^S_{post} = \sum_{i \in \{RN, NN\}} \sum_{\boldsymbol{p} \in \boldsymbol{P}} M^S_i(\boldsymbol{p})$. With the restrictions mentioned earlier and $\dot{M}^S_{RR}(\boldsymbol{p}) = \dot{M}^S_{RN}(\boldsymbol{p}) = \dot{M}^S_{NN}(\boldsymbol{p}) = 0$ for all $\boldsymbol{p}$, we obtain the steady state measures.

2.6 Implications

The model of the seller firm provides the following testable implications.

1. An innovating firm eventually switches to N with a sufficient number of actual customers n_b, provided that the cost for holding actual customers reduces to $\eta_N < \eta_R$.

2. A seller firm does not switch to N immediately after it innovates, since instantaneous profits after the switch are still low due to incompatible customer types.

3. An innovated firm exercises a larger search effort $\sigma_{RN}(\boldsymbol{p})$ and accumulates potential customers p_j prior to the adoption of N.

3 Numerical Example

We show a numerical example of the model introduced in the previous section. We use the parameters presented in Table 1. The retaining cost parameters satisfy $\eta_N < \eta_R$, which gives the new production system N smaller costs for maintaining a buyer. The search cost parameter γ is set $\gamma = 0.2 > 0$. This indicates that having more potential customers alleviates search costs, which is compatible with Eaton et al. (2022). Under these parameter values, a firm's instantaneous profits are maximized at $\boldsymbol{b} = (b_1, b_2) = (14, 0)$ under R and $\boldsymbol{b} = (0, 26)$ under N.

Parameter	Value	Description
J	2	Number of buyer types
ρ	0.04	Discount rate
θ	2	Arrival rate multiplier
(v_1^B, v_2^B)	(0.5, 0.5)	Shares for each buyer types
δ	0.15	Separation rate
k_0	3	Search costs parameter
γ	0.2	Exponent in search costs
c	0.13	Trading costs parameter
η_R	1.6	Exponent in trading costs
η_N	1.5	Exponent in trading costs

Table 1: Parameters: Numerical Example

In the steady state, measures of RN (firms that adopt R with the option of switching to N) are 0 as presented in Figure 1. All firms after the innovation of N are distributed in NN in the steady state as shown in Figure 2. These indicate that all firms that have innovated the production system N eventually switch to the new production system due to the assumption $\eta_N < \eta_R$.

Figure 3 illustrates the steady-state measure of firms RR, which have not innovated the new production system N. Figure 4 depicts the policy function of $x(\boldsymbol{p})$. The blue region represents $\boldsymbol{p}$ values where firms do not transition to the new production system, while firms in the yellow area switch to N. In the steady state, the measure of RR firms has a peak at $\boldsymbol{p} = (5, 4)$, and firms at this point do not switch to N immediately, even after innovating, as shown in Figure 4. Moreover, approximately 73% of RR firms in the steady state choose to stay in production system R just after the innovation of the new production system N. These indicate that some firms that have recently innovated the new production system do not transition to it immediately, even though

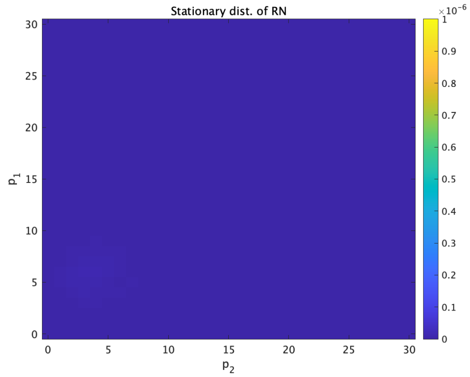

Figure 1: Stationary dist. of RN

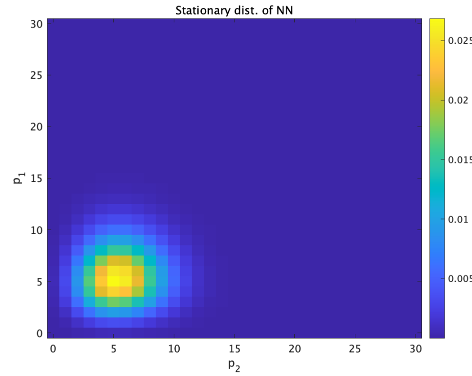

Figure 2: Stationary dist. of NN

they will eventually do so. Firms that have just innovated the new production system N lack customers compatible with N, and their instantaneous profits following a switch are low if they proceed. The incentive to avoid profit declines from hurried transitions accounts for the delay in switching.

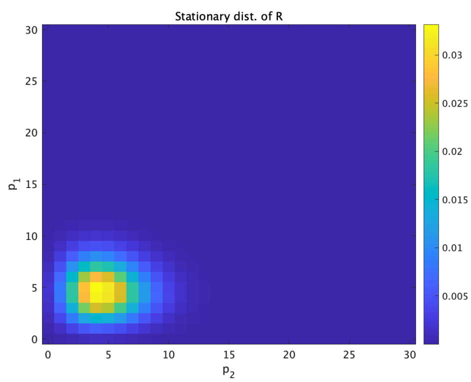

Figure 3: Stationary dist. of RR

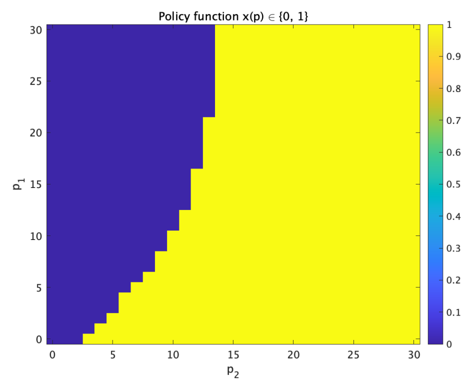

Figure 4: policy of switching

The policy functions of σ_{RR} and σ_{RN} before switching are presented in Figures 5 and 6. Both graphs sliced at $p_1 = 5$ in the staying region of R are shown in Figure 7. The blue and red lines represent σ_{RR} and σ_{RN}, respectively. The search efforts get higher as p_2 increases for both due to $\gamma > 0$, decreasing search costs in the size of the customer base, and the increments are larger when the switch to N is available. We can see that firms that acquire an opportunity to switch to the new production system increase their search efforts to seek more customers and ensure a successful switch in the future.

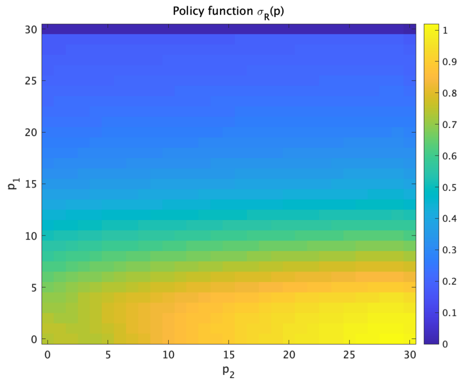

Figure 5: σ_{RR}

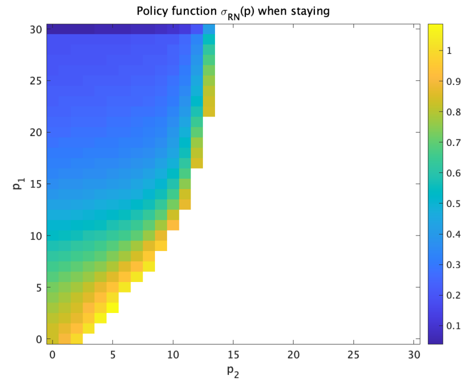

Figure 6: σ_{RN} before switching

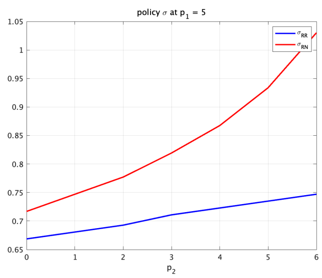

Figure 7: Comparison of σ at $p_1 = 5$

4 Empirical strategy

Motivated by the set of hypotheses our model delineated in the previous section, we empirically investigate firm-level dynamic panel data that includes transaction information. Since we are interested in the effects on a firm's performance and the endogenous behavior associated with changes in the production system, we employ an event-study design following Alfaro-Urena et al. (2022) to capture the time-series pattern of firms switching production systems.

The treatment group consists of firms that switched their production systems only once during the observation period. The control group comprises firms that never changed their production systems during the sample period. For firm i and calendar year t, y_{it} represents the variables of interest observed in the panel data. The elapsed years since the switch for treatment firms are denoted by e, calculated as the difference between the calendar year t and the year of the switch, $year_i^{TPS}$. Thus, e equals zero during the switching period for the treatment firm and in every period for the control group. d_i denotes the dummy variable for the treatment group. The regression equation is then given as follows.

$$y_{it} = \sum_{e=\dots,-1,0,1,\dots} \beta_e(d_i \times \mathbb{I}[t - year_i^{TPS} = e]) + \eta \log(age_{it}) + \kappa_i + \varphi_{it} + \lambda_{ts_i} + \epsilon_{it} \tag{16}$$

The control variables consist of the logarithm of firm age age_{it}, the firm-fixed effect κ_i, the inverse Mills ratio to account for sampling bias due to voluntary reporting or missing data φ_{it}, and the interaction fixed effect involving year t and the two-digit sector s_i, denoted as λ_{ts_i}.

The regression coefficients of our interest are β_e, which represent the effect of the switch on the dependent variable at each elapsed time from TPS, e. We normalize these coefficients at period -1, the year before the switch, and we take the logarithm of some variables. This means that β_e captures the percentage change at elapsed time e relative to one year before the switch.

It is important to note that we cannot capture the causal effect of the switch, as the transition of the production system itself is an endogenous behavior for each firm, and we do not utilize any natural-experimental situation. Instead, we focus on the behavior and performance of the switching firms both before and after the event by capturing the timeline of β_e.

5 Data

5.1 TSR dataset

The empirical analysis utilizing the estimation strategy outlined in the previous section is enabled by the Japanese firm panel data provided by Tokyo Shoko Research, Ltd. (TSR henceforth), a major Japanese credit research company. This dataset contains basic firm information, financial statements, and firm-to-firm relationships concerning business transactions and capital connections, reported annually up to 2024 at the firm level. It encompasses 70% of all Japanese firms, including both listed and non-listed entities.

The firm characteristics especially relevant to our interests are "products handled" and business partner relationships in the dataset. "Products handled" records a firm's products that it produces, classified uniquely by TSR, with up to 6 varieties listed in order of sales for each firm. Business partner information includes a firm's suppliers and customers. A firm lists suppliers and customers, with up to 24 companies having the largest transaction values for each category. In the TSR data, we identify the switch of a production system by a change in a firm's top-selling product to a new product that the firm did not produce in the previous year.

Innovating a new product and replacing the firm's main business requires substantial restructuring, significant changes in the production system and supply chain, and reallocating production resources, which we regard as changes in the production system. In particular, adding a new product to the product mix necessitates the firm seeking new customers, especially when the new product becomes the top-selling product. The firm's product mix data provided by "products handled" enables us to capture the switch.

Since some partnership information is not reported when firms have 25 or more suppliers or customers, we supplement this in the following procedure. If firm A, which has 25 or more suppliers (customers), does not list firm B as a supplier (customer) but B lists A as a customer (supplier), we include B as a supplier (customer) of A. While this procedure alleviates the truncation issue imposed by the limited number of reported partners, we note that we cannot supplement partner information involving two large firms with small transaction volumes, neither of which reports the other as one of the 24 largest business partners. Additionally, we cannot observe the sales volume of each product or the trade volume of each partnership.

5.2 Data description

We limit the samples of manufacturing firms from 2007 to 2023, during which we have business partner data. [1] In particular, we use only firms that report financial statements for at least 10 consecutive periods to avoid biases stemming from a firm's reporting decisions. This restriction excludes firms that report on their business condition at the most favorable time of year, as well as startups whose business models are often unstable and changeable. Moreover, we include only firms that operate in the manufacturing sector for all their observable periods. By doing so, we exclude firms that were once in the manufacturing industry but have converted at least once to the service sector, which accounts for 14.5% of manufacturing firms that have switched their top-selling products. Another 84.4% of switching firms remain in the manufacturing sector in all their reports. After these restrictions, our sample comprises 35,646 manufacturing firms and 525,420

[1] We drop from our sample Non-profit corporations (e.g., NPO), small businesses without corporate registration (e.g., sole proprietor), and pure holding companies.

observations.

Variable "Products handled" includes 36,684 varieties across all sectors, while TSR has 1,269 four-digit SIC codes. Examples of "products handled" include large-scale integration (LSI), semiconductor integrated circuits, telecommunications machinery parts, and electronic equipment components. In TSR, 70% of manufacturing firms are multi-product. In contrast, Bernard et al. (2010) reports that the Longitudinal Business Database in the U.S. exhibits that only 40% of firms are multi-product, implying that TSR uses a more detailed classification. This finer classification of products is useful for detecting a firm's technological shift within an industry.

We focus on the top-selling product switch, a firm's main product turnover. The annual rate of top-selling product switch is approximately 2%, while the overall average is 1.92%. By examining each firm's history with its top-selling product, firms can be classified into three groups: (i) 78.23% of firms did not switch a top-selling product as far as TSR can observe, (ii) another 16.45% of firms underwent a top-selling product switch once after 2007 within our sample period, and (iii) approximately 5% of other firms have undergone a top-selling product switch more than once in our sample. For firms that switched a top-selling product, 35.13% switched their primary product to the previous year's second-largest product, while another 46.76% switched to a new product that they did not produce in the last period. Meanwhile, previous top-selling products remain the second-largest product for 46.51% of firms, whereas they are dropped from the product mix by 29.83%. [2] Especially concerning the switch to a new product (TPS), the annual rate is approximately 0.9%.

The remarkable fact is that in nearly half of the top-selling product switch cases, firms switched their top-selling product to a new product they did not produce in the last year, which suggests that

[2]Since TSR only records up to six products with the highest sales, multi-product firms producing more than six products in the last period may be counted as switching to new products when they switch the top-selling product to those whose sales in the previous year were less than 7th place. Similarly, firms producing more than six products may be considered to have completely dropped the previous top-selling product when they produce it as a product below 7th place. The figures change slightly when we exclude multi-product firms with six or more products. Among the firms that switched a top-selling product, 34.21% switched their primary product to the previous year's second-largest product, and another 50.79% switched to a new product they did not produce last period. Previous top-selling products remain the second-largest product for 46.12% of firms, while they have dropped from the product mix by 33.57%.

significant changes in production technology affecting core products are frequently accompanied by product innovation. Thus, in our narrow definition of a top-selling product switch (TPS), we focus on incidents in which the firm did not produce the new main product in the previous year. Since such a product switch would require a drastic change in the production structure, we regard this behavior as a sign of the switch in the production system, especially when the new top-selling product is a new product that was not produced in the last period.

6 Main findings

This section presents our empirical findings regarding how TPS firms behave and perform before and after TPS. Estimates are obtained using the key regression equation (16) in section 4 for the hypotheses developed in section 2.

We use the sample consisting of (i) firms that have never experienced TPS in the sample period and (ii) firms that experienced TPS once by a new product that was not produced in the previous year of TPS. The former corresponds to the control group and the latter to the treatment group. That is, we exclude firms that underwent TPS more than once to see the long-term impacts of TPS. We have 31,312 firms and 460,691 observations in total. In those observations, 11.14% of firms experienced TPS just once and account for 11.20% of the total sample.

We adopt a narrow definition of treatment (TPS), restricting the top-selling product switch to a new product only. This is because such TPSs indicate a radical change in a production system, yet they account for the largest number of top-selling product switch instances. TPSs require managerial decision-making, whereas switching top- and second-selling products may occur due to temporary or random events.

TPS for a new product also brings a significant change in the customer base. Since the current customers are optimized for the existing product mix, a new product may not necessarily appeal to the existing customer base. When a new product becomes a top seller, the switching firm targets a group of customers distinct from the current ones. Our focus is on such behavior regarding customer acquisition before and after TPS.

6.1 Summary statistics

Table 2 presents the summary statistics of the total sample for the variables of interest. The table includes two indices of customer base diversity: the Simpson and Shannon indices. Let k represent each sector and let Ψ_k denote the set of firms in sector k. Define $p_k = |\Psi_k|/|\bigcup_m \Psi_m|$ as the share of sector k. Then, Shannon's diversity index $D_{shannon}$ and Simpson's diversity index $D_{simpson}$ are defined as

$$D_{shannon} = -\sum_i p_i \log(p_i), \quad D_{simpson} = 1 - \sum_i p_i^2$$

We calculate these indices using the 3-digit SIC of firms in each firm's customer base.

Variable	Mean	S.D.	p25	Median	p75	N
Sales (yen)	6,296,089	93,467,832	68,566	212,061	1,100,530	460,691
Number of Products	2,93	1.64	2	3	4	460,691
Employment (full-time)	95.50	784.62	5	10	33	460,691
Tangible Asset (yen)	1,565,981	20,881,368	4,871	31,113	199,505	460,691
Retirement Allowance (yen)	12,146	401,995	0	0	0	429,379
Marketing Expenditure (yen)	46,351	1,210,120	0	0	60	460,691
Entertainment Expenditure (yen)	2,230	15,883	0	355	1523	460,691
Number of Customers	10.55	38.81	3	5	10	400.858
Addition Rate of Customer	0.18	0.48	0	0	0.2	381,452
Exit Rate of Customer	0.13	0.23	0	0	0.17	381,452
Sales per Customer (yen)	287,167	1,570,056	21,945	56,797	172,844	400,858
Number of Suppliers	16.04	71.68	3	6	12	364,794
Add Rate of Supplier	0.14	0.30	0	0	0.19	346,339
Drop Rate of Supplier	0.11	0.18	0	0	0.17	346,339
Shannon Index of Customer base	0.95	0.76	0	0.95	1.48	352,660
Simpson Index of Customer base	0.48	0.32	0	0.66	0.75	352,660

Table 2: Summary statistics

6.2 Technological change

We first demonstrate that a firm's TPS aligns with a clear change in its product mix and supplier firms. This establishes TPS as an indicator of changes in a firm's production system.

Figure 8 presents changes in the number of products before and after TPS. We observe that the number increases by almost one product. Moreover, we note that 45.8% of TPS firms drop their previous top-selling product from their product mix, while only 35.7% remain producing it as the second largest product. This fact suggests that TPS often involves restructuring a firm's product mix.

Another fact we note is that TPS is associated with supplier churn, i.e., a change in the firm's supplier base. Figures 9, 10, and 11 illustrate the changes in the number of suppliers, the rate of supplier addition, and the rate of supplier exit, respectively. Figure 9 demonstrates the positive impact of TPS on the number of suppliers. We observe that the effect is statistically significant and permanent, as it continues for 10 years. Figure 10 indicates that a new supplier is added during the period of TPS, which naturally results from the permanent increase in the supplier base. Interestingly, we see in Figure 11 that the exit rate of suppliers also rises during TPS, implying that TPS induces supplier turnover. These facts suggest that TPS represents a significant change in a firm's production system that necessitates serious managerial planning.

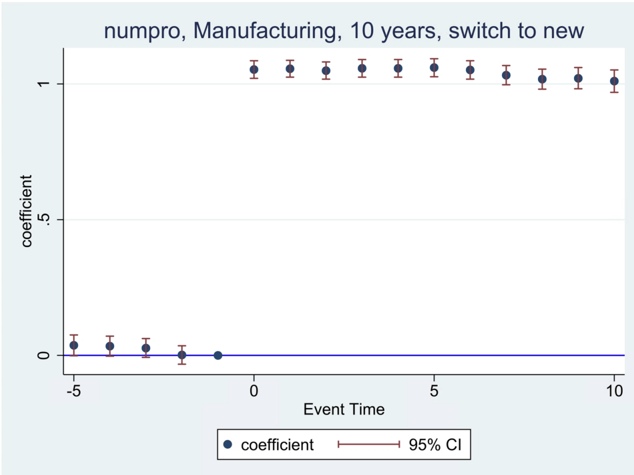

Figure 8: #Products

Figure 9: Suppliers

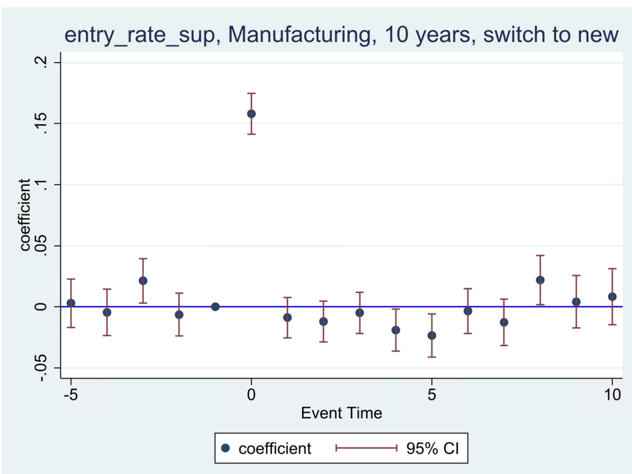

Figure 10: Rate of Supplier Addition

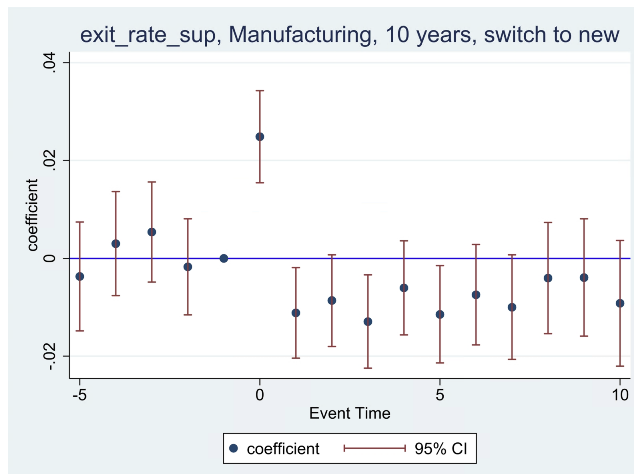

Figure 11: Rate of Supplier Exit

6.3 Customer acquisition

Figure 12 illustrates the timeline of customer numbers. The number of customers experiences a spike of 5% immediately after TPS, and this elevated level remains sustained for at least 5 periods, while no pre-trend is evident. The consistent growth of the customer base right after TPS aligns with our model prediction. The abrupt jump in the number of customers suggests that the TPS firm was anticipating the launch of a new product and preparing for the new production system. Before TPS, the potential number of customers increased in the background. Just after TPS, the number of customers rose as the switching firm began transactions with a new customer base procured in advance.

The interpretation above is supported by the customer churn observed in the data. Figures 13 and 14 illustrate the customer churn: the add rate of customers (#new customers/#previous customers) and the exit rate of customers (#dropped customers/#previous customers), respectively. Both plots indicate a spike in the TPS period, suggesting that customer turnover occurs simultaneously during the switch period. This aligns with our model's behavior, where a firm drops customers compatible with R and adds those compatible with N at once.

Figure 12: Customer

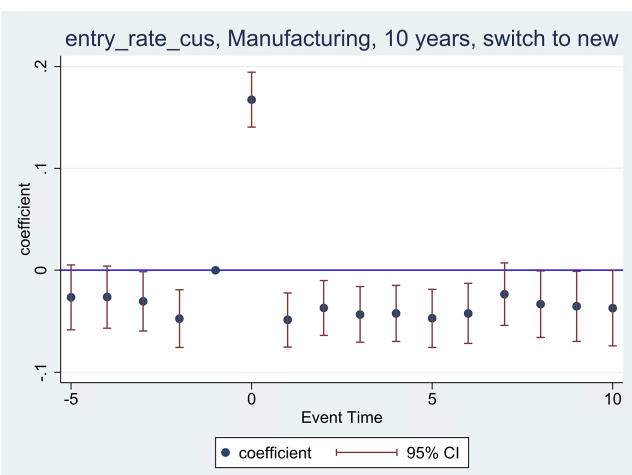

Figure 13: Rate of Customer Addition

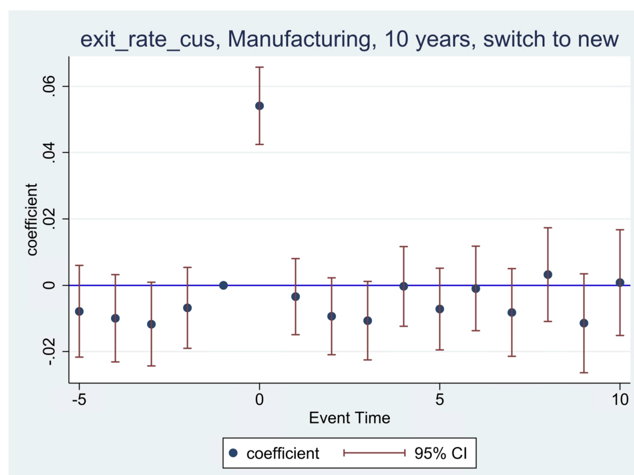

Figure 14: Rate of Customer Exit

The model also shows that the customer base undergoes qualitative changes after the switch.

Figures 15 and 16 illustrate the shift in customer base diversity. The increase in sectoral diversity within the customer base following TPS aligns with our perspective that customers suited to a new production system are qualitatively different from the former customer base.

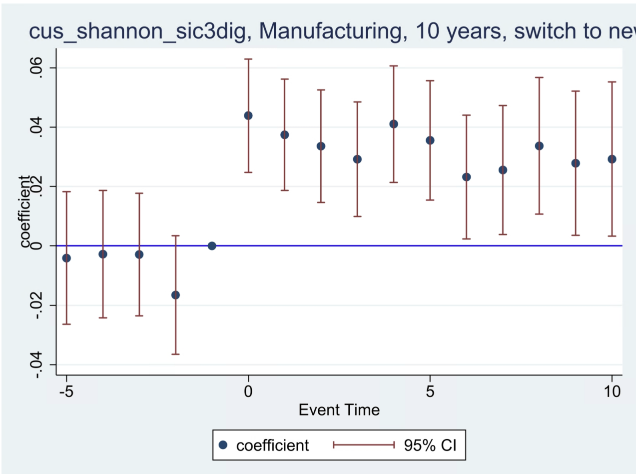

Figure 15: Shannon Index of Customer base

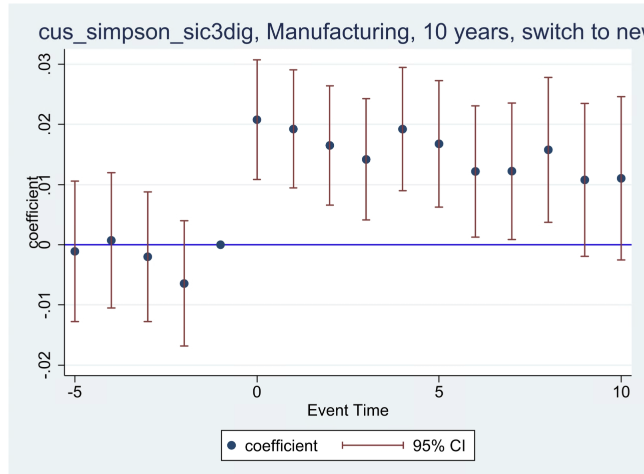

Figure 16: Simpson Index of Customer base

Figure 17 shows that marketing expenditure rises by at least 20% during the preparation periods of TPS, specifically from the -4 period to the 0 period. Figure 18 confirms this finding when controlling for the number of products. The number of products increases after TPS, as indicated in Figure 8. Consequently, marketing expenditure naturally increases following TPS. This accounts for the high level of marketing after TPS in Figure 17 and the insignificant rise in marketing expenditure levels when controlling for the number of products in Figure 18. Nevertheless, both figures illustrate a salient increase in marketing expenditures in the periods leading up to TPS.

As shown in Figure 19, entertainment expenditure also increases before the TPS. Increased entertainment expenses indicate that the company holds more networking events and external business meetings. This aligns with our model, in which the firm considering the switch will spend more on entertainment costs to seek firms that are compatible with the new production system before launching a new product.

These patterns indicate a firm's preparatory behavior: increasing search efforts before TPS to find new customers. The rising pre-trends of marketing and entertainment expenditures support our model prediction that a firm increases search efforts in advance to find new customers before the switch.

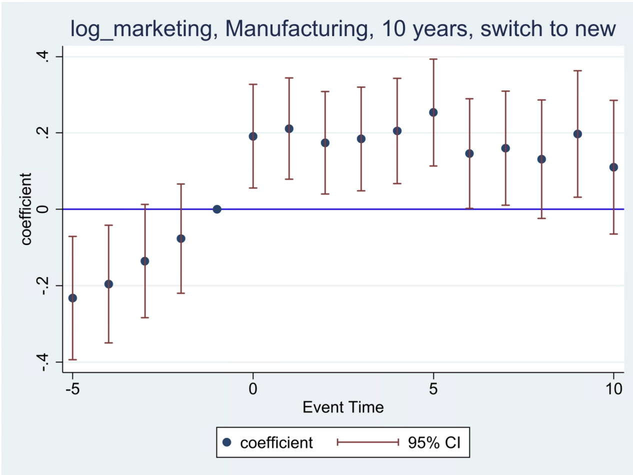

Figure 17: Marketing Expenditure

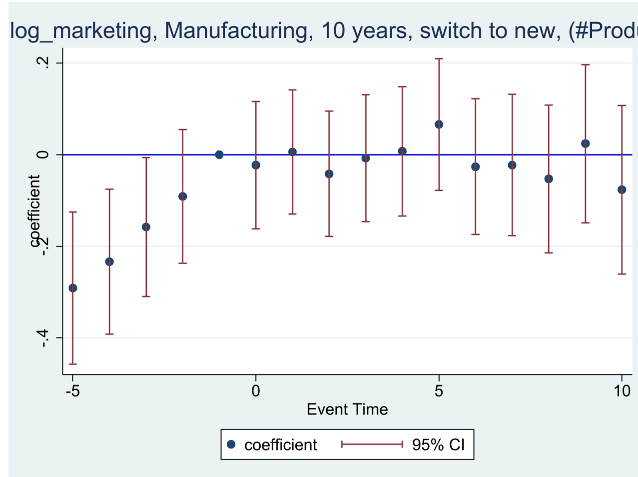

Figure 18: Marketing Expenditure (#Product controlled)

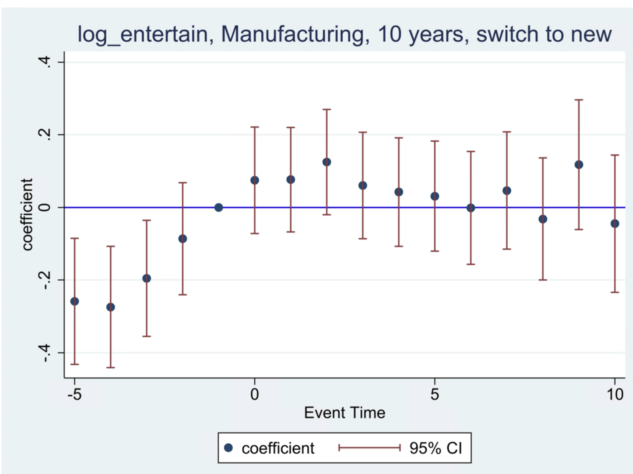

Figure 19: Entertainment Expenditure

6.4 Firm growth due to TPS

Figure 20 shows the timeline of percentage deviations in sales from period -1. Sales have no pre-trend before TPS and are increasing after TPS, which suggests the positive impact of TPS on firm growth.

Figures 21 and 22 illustrate the growth of labor productivity and total factor productivity (TFP). Alongside sales, labor productivity also increases after TPS and grows steadily. In contrast to sales and labor productivity, TFP shows rising pre-trends, with growth also observed after TPS.

This indicates that TPS firms are often expanding or preparing for TPS by enhancing productivity to manage a larger product portfolio following TPS.

Figure 20: Sales

Figure 21: Labor Productivity

Figure 22: TFP

6.5 Job destruction

TPS is interesting from the perspective of creative destruction because it may achieve labor force reallocation within a firm. While an economy-wide workforce reallocation is often costly due to job destruction, a firm's switching of a production system may alleviate the societal cost by reallocating workers internally. To see this, we investigate the timeline for the retirement allowance payment in Figure 23. While we do not observe a pre-trend, the payment increases after TPS. Although the level of employment is maintained after TPS, as shown in Figure 24 [3], it seems that employment replacement outside the firm is inevitable to some extent. Moreover, as in Figure 24, the rising pre-trend in employment also suggests possible preparation for TPS in advance or the possibility of being a growing firm, as the TFP figure implies.

Figure 23: Retire Payment

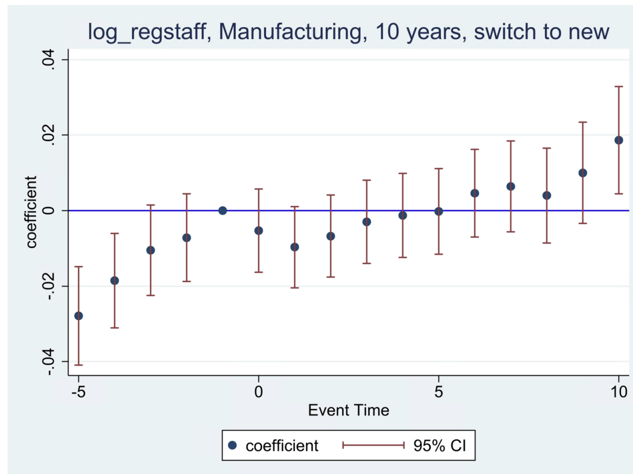

Figure 24: Employment

7 Conclusion

This paper investigates a firm's behavior before and after a drastic shift in its production system using an extensive dataset of Japanese manufacturing firms provided by TSR. In the model part, we specify the problem faced by a firm that innovates a new production system and considers switching to it. The firm seeks potential customers from the frictional market and accumulates the potential customer base. The firm may not switch to the new production system immediately because the firm's previous customer base does not match the new one, which leads to lower profits. To find new customers compatible with the new production system, the firm increases search efforts and delays the switch until an optimal customer base is accumulated.

Our empirical analysis uses the TSR dataset and adopts an event-study design to test the hypotheses generated by the model. We focus on a firm's switch of its top-selling product to a

[3]A caveat is that our employment data indicates the number of full-time employees and does not include contract and part-time employees. Thus, the variation in a firm's employment may be less volatile than that of total employees, including non-regular workers.

new product it did not produce in the previous year, which we call a TPS. A TPS captures a drastic switch in the firm's production system. We empirically establish that a TPS is accompanied by customer churn, i.e., an addition to and an exit from the firm's previous customer base. Furthermore, we find rising pre-trends in marketing and entertainment expenditures before TPS, consistent with the model's predictions on increasing search efforts before the switch of production system and delaying the switch until a sufficient customer base is accumulated.

This paper focuses on firms' customer acquisition behavior following TPS. However, we also observe some impacts of TPS on suppliers. We leave the analysis of the broader implications of TPS on firms' decisions, such as supplier acquisition strategies and research and development activities, for future research. We also provide evidence that TPS firms are experiencing growth in sales and productivity. This suggests that TPS has significant impacts on the growth of individual firms. However, TPS is rare, with the share of TPS firms being approximately 0.9% of all firms each year. Further investigation into the effects of TPS on aggregate growth is necessary for future research.

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