Product and Process Innovation: Determinants and Dynamic Effects on Firm Growth*

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Abstract

Product and process innovations—defined as the introduction of new goods or services and improvements in production processes, respectively—have differential impacts on firm performance. Using firm-level microdata on innovation surveys and financial statements, our empirical analysis yields two key findings. First, the increasing prevalence of process innovation over product innovation has been observed over the past two decades across European countries and Japan, with this trend particularly strong in Japan. Second, higher market growth leads firms to prioritize product innovation, which in turn, increases firm sales and employment over several years, whereas process innovation does not exhibit this pattern. This suggests that product innovation plays a greater role in macroeconomic growth than process innovation by reinforcing the interaction between firms' innovation strategies and expanding market demand. The absence of this mechanism may have been a factor contributing to Japan's sluggish economic growth.

Keywords: Economic growth, Productivity, Product innovation, Process innovation

JEL Classifications: D22, L1, L25, L53, O25, O31

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1 Introduction

Innovation is widely recognized as a fundamental driver of economic growth. Among various types of innovation, product and process innovations—defined as the introduction of new goods or services and improvements in production processes, respectively—have differential impacts on firm performance (Griffith *et al*., 2006; Hall, Lotti, and Mairesse, 2008; Hall, Lotti, and Mairesse, 2009; Harrison *et al*., 2014). Our cross-country analysis indicates that over the past two decades, the increasing prevalence of process innovation over product innovation has been observed across European countries and Japan, with this trend particularly strong in Japan and evident across a wide range of industries (Figure 1). Furthermore, recent studies suggest a potential link between Japan's prolonged low growth and its emphasis on process innovation (Fukunaga *et al*., 2024). These findings highlight the need to further examine the mechanisms driving firms' innovation choices and their medium- to long-term macroeconomic consequences.

To the best of our knowledge, no prior research has analyzed the dynamic impacts of innovation, due to the lack of longitudinal data. Innovation surveys are typically conducted at intervals of three years, collecting information on whether firms have implemented innovations since the previous survey (Hall, 2010; OECD and Eurostat, 2018). Furthermore, they do not track the same firms over time. As a result, prior studies have relied on cross-sectional data analysis (Mohnen and Hall, 2013), making it difficult to examine the medium- to long-term effects of innovation, even though the timing of these effects has been recognized as a crucial factor in measuring their impact. For instance, learning effects (Mohnen and Hall, 2013) and disruptions in product life cycles (Roper *et al*., 2008) can create time lags before innovation impacts are reflected in firm performance. Moreover, product and process innovations often interact in complementary ways, influencing firm performance over extended periods (Berlingieri *et al*., 2024). These timing issues may contribute to inconsistencies in the reported magnitude and direction of innovation's effects across studies (Morris, 2018). Despite these insights, limited attention has been paid to the dynamic impacts of different types of innovation, underscoring the need for panel data analysis.

This study addresses these gaps by integrating innovation survey data with firm-level financial panel data, effectively overcoming the aforementioned data constraints. Using our datasets, we estimate the dynamic impacts of product and process innovations on firm-level sales, employment, markup, and labor productivity (LP), explicitly considering firms' competitive environments and market growth. To ensure causal effects of innovation, we employ propensity score and doubly robust estimator (DR estimator), a widely used

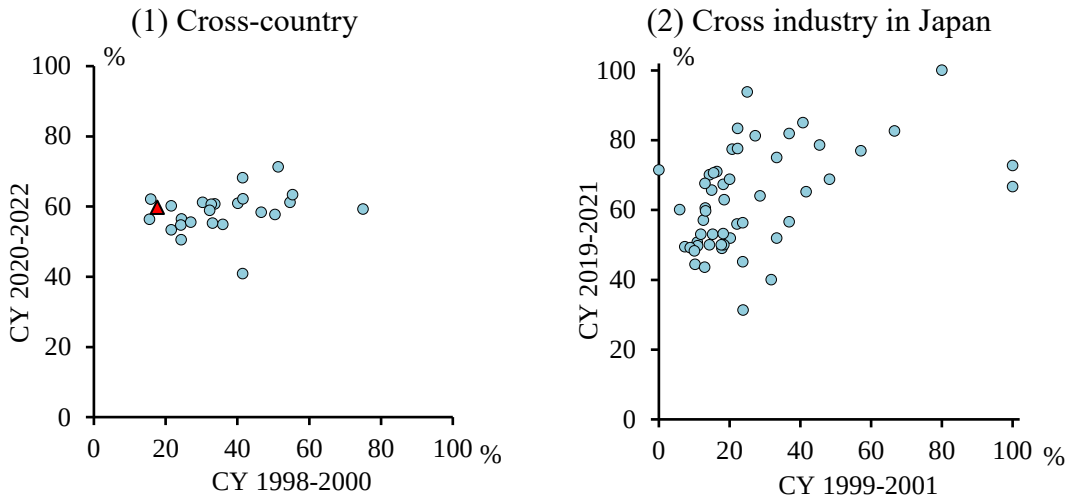
method in the causal inference literature (Imbens and Rubin, 2015; Callaway and Sant'Anna, 2020), controlling for a broader range of confounding variables than prior studies that rely solely on innovation surveys.

The key findings are as follows. First, we find that moderate competition fosters innovation, as suggested by previous studies (Aghion *et al*., 2005; Hashmi, 2013; Igami and Uetake, 2020; Griffith and Van Reenen, 2022). Importantly, we observe no substantial differences between product and process innovations in this regard, indicating that competition broadly encourages both types of innovation. Second, we find that industry-level sales growth rates—used as a proxy for market growth—enhance the probability of product innovation, whereas no such relationship is observed for process innovation. Third, while product innovation increases firm sales and employment over several years, process innovation does not exhibit this pattern.

These findings suggest that the interactions between firms' decisions on innovation types and market growth play a crucial role in shaping macroeconomic outcomes. Specifically, a lack of market growth within industries may contribute to a trend toward process innovation, which in turn could have been a factor contributing to Japan's sluggish economic growth. From a policy perspective, shifting the balance toward product innovation could provide sustained upward pressure on economic growth. This can be achieved, for example, by promoting new market-creating products and the development of breakthrough technologies, rather than only supporting labor-saving automation and supply chain optimization.

The remainder of this paper is structured as follows. Section 2 describes the data sources. Section 3 presents the empirical methodology, detailing the measurement of innovation indicators, the estimation of innovation implementation probabilities, and the estimation of the dynamic causal effects of innovation on firm performance. Section 4 presents the main findings and their implications. Section 5 concludes.

(Figure 1) Process innovation ratio across countries and industries



Note: Panel (1) illustrates the changes in the process innovation ratio (the ratio of the number of firms implementing process innvation to the total number of firms implementing either product or process innovation) across the 24 European countries and Japan. In the plot, the red triangle indicates the Japanese data and the other blue markers indicate other countries. Panel (2) illustrates the changes in the process innovation ratio for each industries in Japan.

Sources: Eurostat; OECD; MEXT.

2 Data

Our analysis is based on firm-level microdata from two government surveys in Japan. The first dataset is the Japanese National Innovation Survey (J-NIS)[1], which collects information on firms' innovation activities, including product and process innovation, the number of competing firms, and factors influencing innovation decisions. J-NIS basically investigates firms' innovation implementation over three years for multiple survey waves,[2] and it collects data from companies with 10 or more employees. In the J-NIS, an innovation was classified into "process innovation" and "product innovation".

The Second dataset is the Basic Survey of Japanese Business Structure and Activities (BSJBSA), which provides comprehensive firm-level information on financial statements, employment, investment (including R&D expenditure), and other business activities.

[1] J-NIS have been conducted intermittently by Ministry of Education, Culture, Sports, Science and Technology (survey years are as follows; 2003, 2009, 2013, 2015, 2018, 2020, 2022). This survey is based on the international guidelines, Oslo manual 2018 (OECD and Eurostat, 2018).

[2] In J-NIS, each firms answers based on the last 3 years achievement except for the survey in 2009. In 2009 survey, answers are based on the last 1 year.

BSJBSA is an annual survey for all firms whose capital are above 30 million Yen or whose employees exceed 50 people. This survey is the Fundamental Statistical Survey in Japan and each enterprise is obliged to report accurately.

By linking these two datasets at the firm level, we construct a panel dataset. We matched each firm data in each year according to firm names or firm identifiers designated by National Tax Agency. Table 1 presents the sample sizes before and after merging the datasets. While each dataset contains a larger number of observations individually, the final merged sample includes approximately 1,000 to 4,000 firms per survey wave.

(Table 1) Number of samples in the statistics surveys and matched sample size

Year	BSJBSA, METI		J-NIS, MEXT		
	Population	Realised Samples	Sample Size	Realised Samples	Matched with BSJBSA
2003	38,481	27,545	43,174	9,257	2,417
2004	38,133	27,055			
2005	37,786	28,340			
2006	38,688	27,677			
2007	38,430	27,917			
2008	38,276	29,080			
2009	38,042	29,355	15,137	4,579	1,722
2010	36,843	29,096			
2011	37,600	29,570			
2012	37,876	30,647			
2013	37,523	30,584	20,191	7,034	1,614
2014	37,025	30,217			
2015	37,404	30,180	24,825	12,526	1,602
2016	37,606	30,231			
2017	37,466	30,151			
2018	37,310	29,530	30,280	9,439	2,366
2019	37,528	29,780			
2020	37,162	29,295	31,088	12,534	3,929
2021	36,294	29,574			
2022	44,812	34,056	31,971	13,181	4,095

Note: This table shows that summary of the statistics in each survey year and realized sample size matched by firm name and firm number. Because BSJBSA is complete enumeration, “population” means firms who accept questionnaires and “realized samples” means firms who answer the form. In J-NIS, “realized samples” indicates the number of firms in sampling population who actually fills out the survey form.

Sources: METI, MEXT.

3 Method

3.1 Innovation Indicators

To analyze surrounding conditions of firms in Japan, we introduce three indicators about innovation; process innovation rate, product innovation rate, and process-only innovation ratio. The process (product) innovation rate is as follows,

$$R_{proc,t} = \frac{N_{proc,t}}{N_t}, \qquad R_{prod,t} = \frac{N_{prod,t}}{N_t}, \tag{1}$$

where N_t is the number of firms investigated by the survey in year t. A survey conducted in year t aims at a periods from $t-3$ to $t-1$. $N_{proc,t}$ ($N_{prod,t}$) is the number of firms implementing the process (product) innovation at least once. We also define $N_{proc-only,t}$ as the number of firms implementing only process innovation. Therefore, dividing $N_{proc-only,t}$ by the total number of firms who conduct innovations ($N_{innov,t}$), the process-only innovation ratio, $R_{proc-only,t}$, represents the share of process innovation;

$$R_{proc-only,t} = \frac{N_{proc-only,t}}{N_{innov,t}} \tag{2}$$

3.2 Probit Estimation

Previous studies on measuring the effects of innovation, originating from Crépon, Duguet, and Mairesse (1998), have utilized cross-sectional data to estimate the likelihood of innovation implementation and its effects. We build upon this approach to capture the relationship between medium- to long-term financial variables and innovation implementation. First, we explain how we estimate determinants of innovation implementation using probit model. After that, in section 3.3, we newly introduce the concept of dynamic causal effects of innovation implementations.

To investigate the determinants of innovation implementation, we estimate a probit model in which the probability of innovation implementation is explained by key firm-level and environmental factors. Specifically, we estimate the following equation:

$$P\{Innov_{x,i,t} = 1\} = \Phi(\beta_0 + \beta_1 Comp_{i,t} + \beta_2 Growth_{j,t-1} + \boldsymbol{Z}_{i,t-1}\boldsymbol{\gamma} + \alpha_t + \lambda_j + \delta_r + \epsilon_{i,t}). \tag{3}$$

Here, $Innov_{x,i,t}$, represents whether firm i has implemented either product or process

innovation (but not both simultaneously) in three year periods starting from t to $t+2$. $\Phi(\cdot)$ represents the cumulative distribution function of the standard normal distribution. The key explanatory variable $Comp_{i,t}$ captures the degree of market competition faced by firm i in year periods starting from t to $t+2$ as a categorical variable. Specifically, firms are classified into four groups based on the number of competitors: monopoly (zero competitors), oligopoly (1–5 competitors), moderate competition (6–14 competitors), and excessive competition (15 or more competitors). $Growth_{j,t-1}$ measures the firm's growth rate over the past three years. The control variables, $\boldsymbol{Z}_{i,t-1}$, are derived from linked financial data and include firm age, the logarithm of sales, the logarithm of real labor productivity, the logarithm of R&D investment per employee, the average borrowing interest rate (calculated from interest payments and outstanding debt), and the leverage ratio (debt-to-total-assets ratio). These variables are primarily obtained from financial data linked to the innovation survey. Compared to previous studies that controlled for only those firm characteristics available in the innovation survey, our approach allows for a more rigorous treatment of potential endogeneity concerns, leading to more reliable estimation results.

To account for unobserved heterogeneity, we include survey year fixed effects (α_t), industry fixed effects (λ_j), and regional fixed effects (δ_r). Finally, $\epsilon_{i,t}$ denotes the error term.

3.3 Estimating Causal Effects

To quantify the dynamic effects of innovation on firm performance, we estimate the Average Treatment Effect on the Treated (ATT) at different time horizons following innovation implementation. In this context, treatment refers to the implementation of either product or process innovation during three year periods, but not both simultaneously, meaning that a firm is considered treated if it has implemented only one type of innovation. The ATT for innovation type x is defined as follows:

$$ATT_{x,h} = E\left[Y_{i,h}(1) - Y_{i,h}(0) \middle| Innov_{x,i,t} = 1\right], \quad (4)$$

where $Y_{i,h}(1)$ and $Y_{i,h}(0)$ respectively represent the potential outcomes with and without innovation when h years have passed after the innovation implementation, and $Innov_{x,i,t} = 1$ indicates that firm i engaged in innovation type x (either product or process innovation, but not both) at time periods from t to $t+2$. The outcome variables used in this analysis include the growth in the number of employees, real labor productivity

(LP), and sales, as well as the change in markup. Real LP is calculated as real value-added per employee. Real value-added is obtained by deflating nominal value-added using the value-added deflator from The Research Institute of Economy, Trade and Industry (RIETI). Markup is measured as the ratio of sales to operating costs.

To estimate ATTs, we employ Doubly Robust estimation method (DR), which combines a outcome regression model to a propensity score model. The DR estimator is accurately estimated when either model's specification is correct. In this formulization, we use the previously estimated probit model to estimate the propensity scores for product and process innovations to control for selection bias, ensuring that treatment assignment is appropriately balanced across firms with similar characteristics.

The doubly robust ATT in time horizon h after innovation implementation, which is calculated for each innovation type x estimator, $ATT_{x,h}^{DR}$ is given by:

$$\begin{aligned} ATT_{x,h}^{DR} &= \hat{E}^{DR}\left[Y_{i,h}(1) - Y_{i,h}(0)\middle| Innov_{x,i,t} = 1\right] \\ &= \frac{1}{N_{1,h}}\sum\nolimits_{i\in T} y_{i,h} - \left(\frac{\sum_{i=1}^{N} e_{i,t}\, g(z_i, \hat{\gamma}_1)}{\sum_{i=1}^{N} e_{i,t}} + \frac{\sum_{i\notin T}\left[\frac{e_{i,t}}{1-e_{i,t}}\left(y_{i,h} - g(z_i, \hat{\gamma}_1)\right)\right]}{\sum_{i\notin T}\frac{e_{i,t}}{1-e_{i,t}}}\right), \end{aligned} \tag{5}$$

where $N_{1,h}$ is the number of treated firms (i.e., firms that realized only one type of innovation), T represents the set of treated firms, and $e_{i,t}$ is the propensity score for firm i. A function $g(\cdot)$ is defined as:

$$g(\boldsymbol{z}, \gamma_1) = E\left[Y_1\middle|\boldsymbol{z}, Innov_{x,t} = 1\right], \tag{6}$$

where $\boldsymbol{Z}$ is the vector of covariates and $\hat{\gamma}_1$ is the vector of their coeffcients of the treatment group. $g(\cdot)$ denotes a regression model for the control group and we substitute covariates $\boldsymbol{Z}$ of the control group in this model. It enables to infer the counterfactual values if firms in the treatment group did not implement an innovation based on the value of the realized value of firms in the control group.

To calculate a confidence interval of DR-ATT, we adopt nonparametric method; bootstrap calculation. We randomly sample the data with replacement until this new sample size coincides with the sample size of original dataset, and we repeat this procedure 200 times to obtain the 95% (68%) confidence interval and mean estimate of ATT.

By applying this approach, we ensure that the estimated effects are robust to time-varying confounders and heterogeneous treatment timing, making it well-suited for analyzing the dynamic impacts of innovation.

4 Results

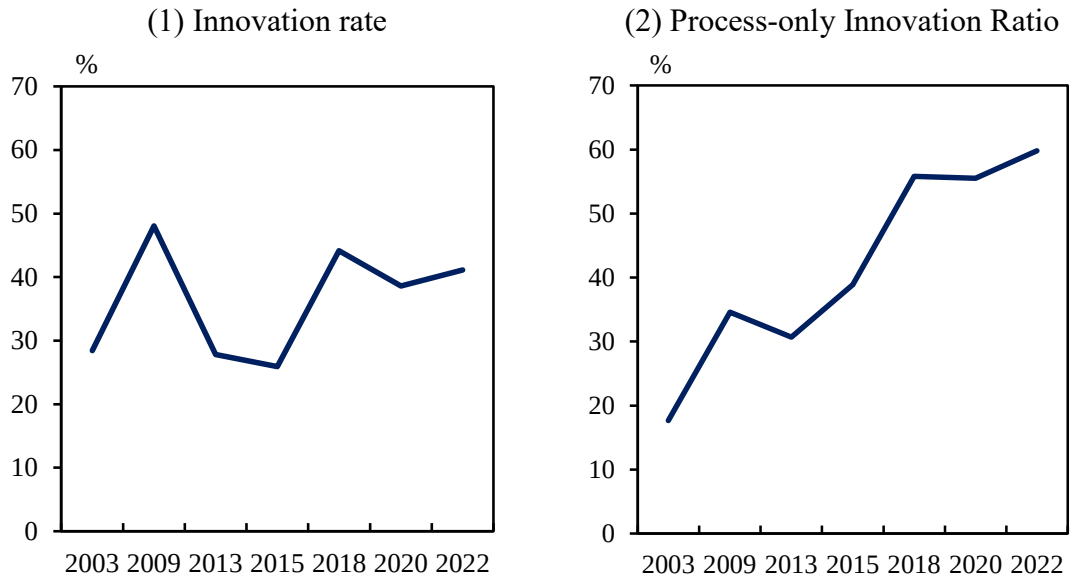
We analyze how innovation modes change in Japan last 20 years, what promotes a innovation, and strength and persistency of innovation effect on firm performances. First, we shed light on the extent to which Japanese firms had demonstrated a commitment to process innovation across the year. Second, we explored factors which contributed to firm's innovation in terms of competitors and firm specific conditions such as financial properties or industrial growth expectations. Finally, we identified the average treatment effects of innovation on the firm's performances along the time series.

4.1 Basic Facts

From 1999-2021, the number of firms that only pursued process innovation had been increasing in Japan. In Figure 2, the proportion of firms that conducted any type of innovation had remained stable around 40%. On the other hand, the ratio of firms that only conducted process innovation had increased about 3 times in 20 years (Figure 2 (2)). It indicates that firms who do not prefer the product innovation has been increasing and they tend to select the product innovation recently. Although these patterns were consistent even if types of industries and firm size varied (Figure 3), the gratitude of increasing were different. Firms who employed more people were not inclined only to implement process innovation. In addition, compared to the manufacturing industry, non-manufacturing industry represented a discontinuous increase.[3]

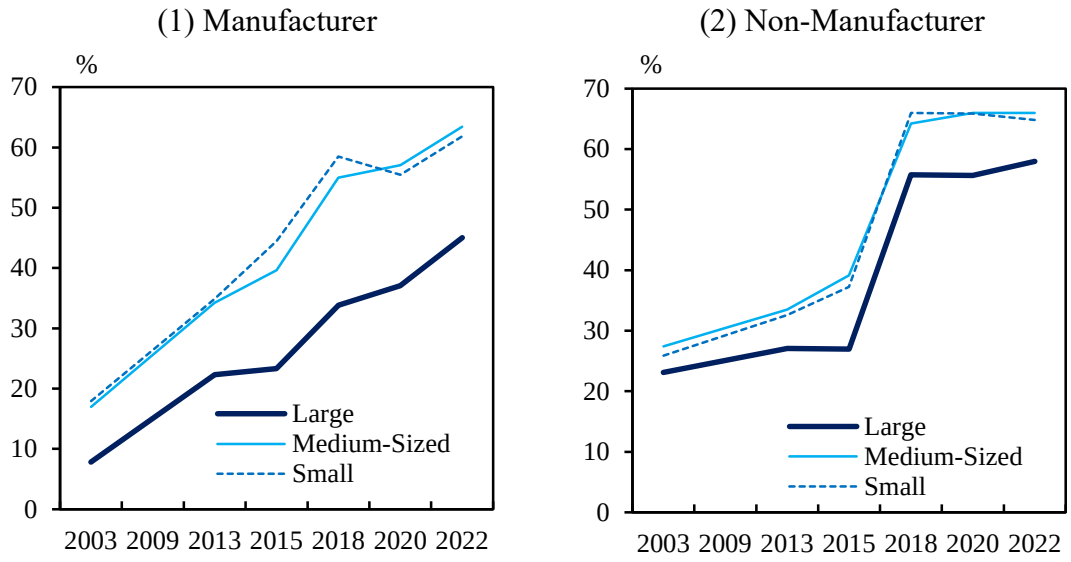
[3] This discontinuity may stem from the contents of questionnaire. From 2015, The J-NIS survey explicitly include the improvement of office work efficiency such as digital transformations in the definition of process innovation. This extensiton of definition could lead to potive answer of non-manufacturing companies.

(Figure 2) Time Series of Process or Product Innovation Rate



Note: Panel (1) shows that the ratio of firms who conduct either type of innovation, process or product. The x axis means a year range which each survey focuses on. For example, the left side point of this plot represents that innovation rate are measured based on the achievements from CY 1999 to 2001.In addition, most of surveys were conducted based on calendar year, while some survey (in 2009, 2013, 2015) were based on financial year. Panel (2) illustrates the dynamics of process-only innovation ratio in each survey period.

(Figure 3) Process-only Innovation Ratio with Different Industiries and Firm Size



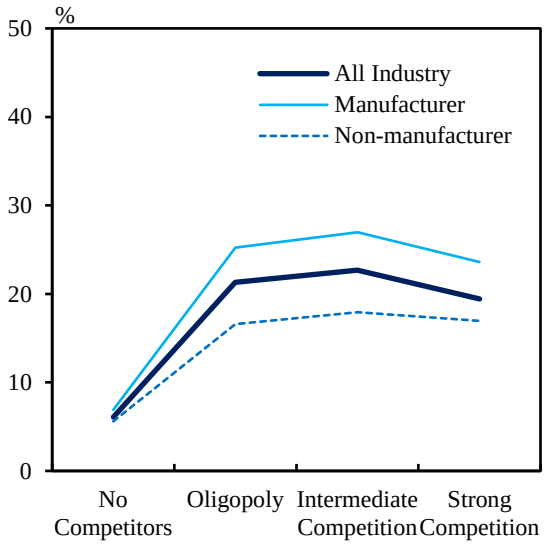
Note: We determine whether a firm is classified into manufacturing or non-manufacturing based on Japan Standard Industrial Classification (JSIC). Firm size are classified into three types by the number of employees; the lower threshold is 49, the higher one is 249 people.

Existence of competitors also affected the firm's innovation behavior. Although the product innovation rate were always lower than the process innovation rate, their shapes of changes along with competitiveness gradients were similar (Figure 4). Both innovation rate curve were depicted by inverted-U shape or saturation curve. When firms had no competitors, both innovation rates were lowest among other competitive conditions. In addition, under the strong competition, which the number of competitors was 10 or more, innovation rate often decreased rather than under intermediate competition.

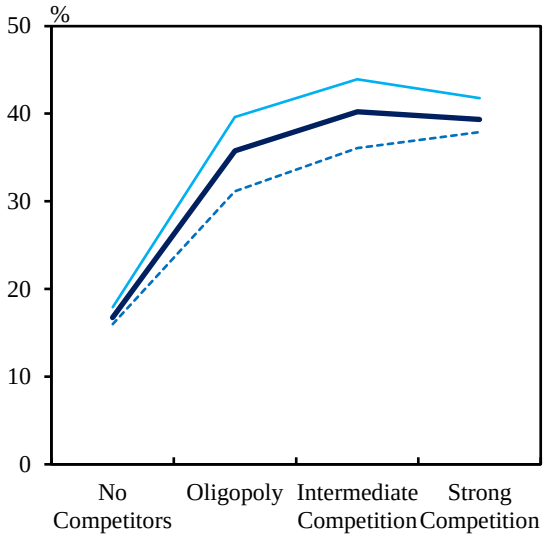
In Figure 5, the process-only innovation ratio is lowest in the oligopoly situation, contrast to its gradual increasing of the level. Process-only innovation ratio were highest among the firms which had no competitiors. We explored that although innovation itself was not likely to occur under monopoly and strong competition, commitment to process innovation was likely to occur.

(Figure 4) Product and process innovation rate under different competitive environments

(1) Product innovation

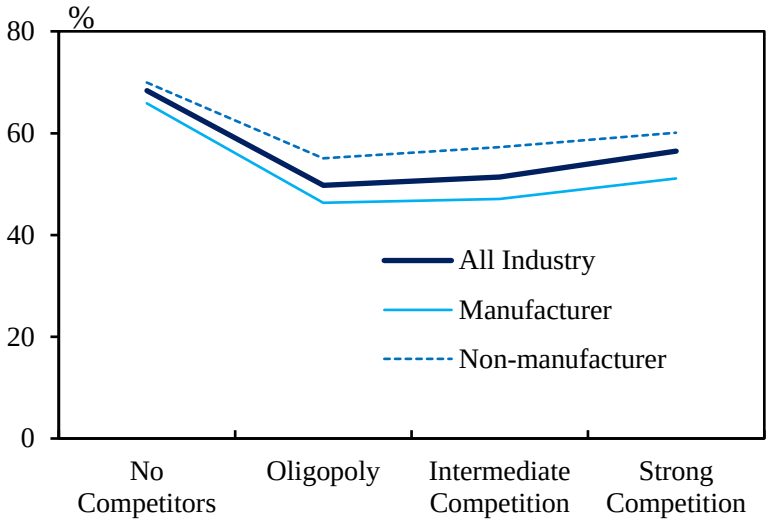


(2) Process innovation



Note: The number of competitors for each competition category on the horizontal axis is defined as follows. No Competitors: 0, Oligopoly: 1-5 (1-4), Less Competitive: 6-14 (5-20), More Competitive: 15- (21-). The survey in 2009 is based on the number of competitors shown in parantheses above. The values are calculatioed for four surveys (2009, 2018, 2020, and 2022).

(Figure 5) Process-only innovation ratio under different competitive environments

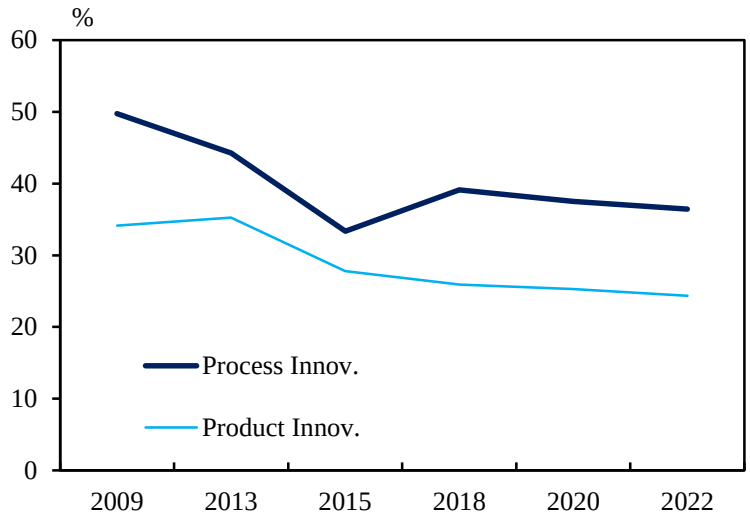


Note: The number of competitors for each competitiveness on the horizontal axis is defined as follows (the definition in 2009 survey is different and is shown in parantheses). No Competitors: 0, Oligopoly: 1-5 (1-4), Less Competitive: 6-14 (5-20), More Competitive: 15- (21-).

In the last of this section, we analyzed the frequency of innovation implements (Figure

6). The proportion of firms that conducted an innovation but not twice in a row for two consecutive surveys exhibited a slight downward trend. In addition, process innovation was likely to occur intermittently than product innovation.

(Figure 6) The ratio of firms who conduct innovation intermittently



Note: We illustrates the rate of firms which answer differently on two adjacent surveys for innovation implementation. Each point of x-axis represents comparison of two survey years. For example, “2003-2009” means that what percentages of firms who implemented innovation in 2003 survey also coducted the innovation in 2009 survey.

4.2 Determinants of Innovation Implementation

Using the probit regression model, we identified determinants of innovation implementation and estimated their magnitude. Probit regression are conducted for process-only innovation and product-only innovation respectively (Table 2, 3). For each regression result, we adopted the model using AIC.

For process-only innovation, there were three main features (Table 2 (4)). First, strength of competition had a positive effect on a innovation implementation. Compared to the situation with no competitiors, the coefficients were significantly larger when the number of competitors was medium or higher. In addition, the effect of competition showed the largest impacts on the innovation realizing among the all indepedent variables. Second, age and R&D expenditure had negative coefficients. Elder firms was not apt to innovate only processes and growth of R&D expenditure had negative effects on process-only innovation. Third, financial conditions of a firm had significant impacts on innovation.

Higher interest rate caused decreasing of the process-only innovation implement. On the other hand, leverage ratio had a positive effect on the probability of process-only innovation. In other words, larger debts contributed to process-only innovation.

In the case of product-only innovation, whereas the impact of competition was similar to the impact on process-only innovation, other variables affectd differently. Industry growth rate and firm sales had significant effects only on the product-only innovation. Industries that a firm belonged growed more rapidly, the probability that the firm realized product-only innovation became larger. Secondly, in contrast to the process-only innovation, age and R&D expenditure demonstrated a positive effect on product-only innovation. The product-only innovation was easily to occur when a company invested largely on R&D or their age was young.

(Table 2) The Probit estimation: determinants of process innovation

	(1)	(2)	(3)	(4)
No. of Competitors: 1-5	0.1329***	0.1331***	0.1349***	0.1348***
	(0.0392)	(0.0401)	(0.0400)	(0.0403)
No. of Competitors: 6-14	0.1476***	0.1472***	0.1500***	0.1489***
	(0.0321)	(0.0339)	(0.0327)	(0.0340)
No. of Competitors: 15-	0.1306***	0.1327***	0.1331***	0.1348***
	(0.0342)	(0.0353)	(0.0348)	(0.0355)
Industry Growth Rate (past 3 years)	-0.0015	-0.0014	-0.0016	-0.0015
	(0.0014)	(0.0015)	(0.0014)	(0.0015)
log(Age)		-0.0002		-0.0001
		(0.0003)		(0.0003)
log(Sales)*1,000	0.0017***	0.0017***	0.0016***	0.0016***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(LP) *100		-0.3232		-0.2860
		(0.0022)		(0.0023)
log(R&D Expenditure /Employee) *100		0.0088***		0.0092***
		(0.0000)		(0.0000)
Interest Rate			-0.0283***	-0.0300***
			(0.0100)	(0.0095)
Levarage Ratio			0.0006***	0.0006***
			(0.0001)	(0.0002)
Fixed Effects				
Industries	Y	Y	Y	Y
Years	Y	Y	Y	Y
Regions	Y	Y	Y	Y
N	9,803	9,799	9,803	9,799
AIC	11,354	11,342	11,350	11,337
AUC	0.69	0.69	0.69	0.70

Note: This table reports the estimation results from a probit model across 4 patterns of variable sets. *, *, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

(Table 3) The Probit estimation: determinants of product innovation

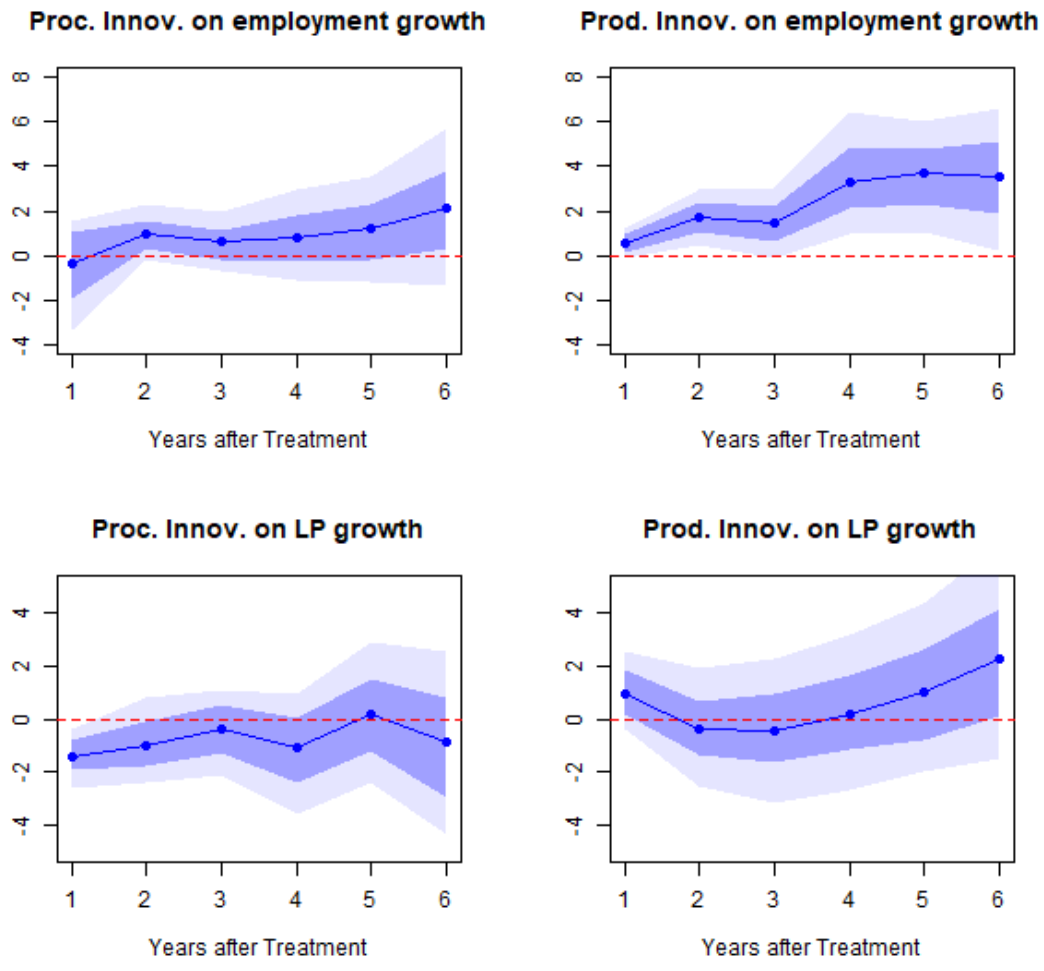
	(1)	(2)	(3)	(4)
No. of Competitors: 1-5	0.2360***	0.2386***	0.2311***	0.2374***
	(0.0753)	(0.0683)	(0.0716)	(0.0660)
No. of Competitors: 6-14	0.2377***	0.2398***	0.2329***	0.2386***
	(0.0775)	(0.0748)	(0.0750)	(0.0728)
No. of Competitors: 15-	0.1965**	0.2101**	0.1923**	0.2090**
	(0.0880)	(0.0886)	(0.0850)	(0.0865)
Industry Growth Rate (past 3 years)	0.0018*	0.0018*	0.0019*	0.0018*
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
log(Age)		0.0008***		0.0007**
		(0.0003)		(0.0003)
log(Sales)*1,000	0.0026***	0.0020***	0.0027***	0.0020***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(LP) *100		-0.1937		-0.2213
		(0.0029)		(0.0029)
log(R&D Expenditure /Employee) *100		0.0251***		0.0249***
		(0.0000)		(0.0000)
Interest Rate			0.0168*	0.0081
			(0.0088)	(0.0089)
Levarage Ratio			-0.0010***	-0.0004
			(0.0003)	(0.0004)
Fixed Effects				
Industries	Y	Y	Y	Y
Years	Y	Y	Y	Y
Regions	Y	Y	Y	Y
N	8,160	8,156	8,160	8,156
AIC	7,131	6,899	7,125	6,901
AUC	0.72	0.75	0.72	0.75

Note: This table reports the estimation results from a probit model across 4 patterns of variable sets. *, *, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3 Innovation Impacts on Firm Performance

In this section we estimate ATTs to capture the cummurative dynamic effects of innovation using propensity scores drived from model specification in Table 2(4) and 3(4). The results for firm employment and labor productivity growth rate are presented in Figure 7. Each panel in figure indicated that strength of effects varied by time. While the process innovation did not have a significant effect on employment, the product innovation had a sufficient positive effect. The positive effect of product innovation had gradually appeared and it was maximized 5 years later after an innovation happened. On the other hand, neither type of innovation had significant effects on LP.

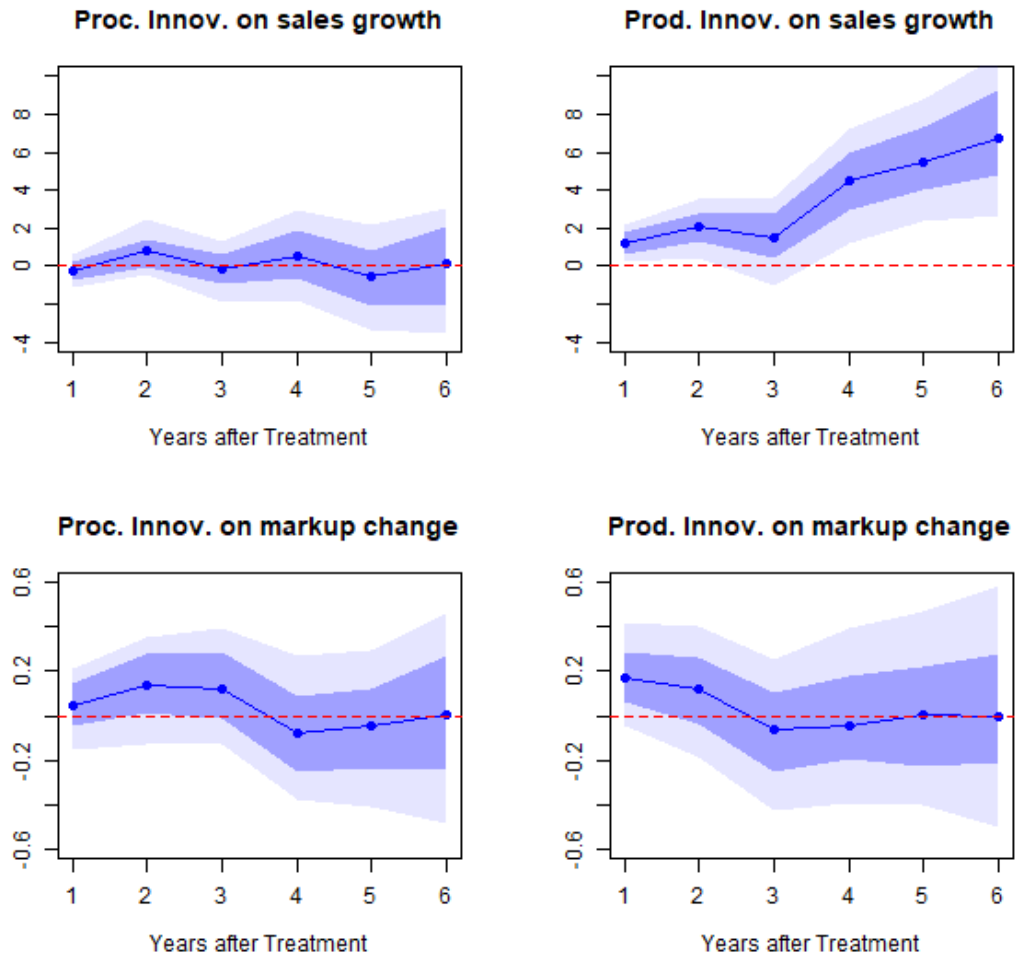
(Figure 7) Cumulative effects of innovation on employment and LP growth



Note: This figure shows the estimated cumulative effects of innovation on firms' employee growth rates and sales growth rates, measured by doubly robust ATT. The dark and light shaded areas indicate the 68% and 95% confidence bands, derived from the percentiles of 200 estimates using the bootstrap method.

We also estimated innovation effects on changes of sales and markup (Figure 8). The effect of innovation on sales growth were significantly prominent when a product innovation was implemented. Process innovation increased sales growth by 7% over 6 years on average. In contrast, process innovation did not clearly raise sales.

(Figure 8) Cumulative effects of innovation on sales growth and markup change



Note: This figure shows the estimated cumulative effects of innovation on firms' employee growth rates and sales growth rates, measured by doubly robust ATT. The dark and light shaded areas indicate the 68% and 95% confidence bands, derived from the percentiles of 200 estimates using the bootstrap method.

5 Conclusion

This study examines the determinants and dynamic impacts of product and process innovations by integrating innovation survey data with firm-level financial panel data. Our analysis highlights several key findings. First, moderate competition fosters innovation, as

suggested by previous studies, with no substantial differences between product and process innovations in this regard. Second, industry-level sales growth rates, which serve as a proxy for market growth, enhance the probability of product innovation, whereas no similar relationship is observed for process innovation. Third, while product innovation increases firm sales and employment over several years, process innovation does not exhibit this pattern.

These findings provide important insights into the interactions between firms' innovation decisions and market growth. Specifically, a lack of market growth within industries may contribute to a trend toward process innovation, which in turn could have been a factor contributing to Japan's sluggish economic growth.

From a policy perspective, shifting the balance toward product innovation could provide sustained upward pressure on economic growth. This can be achieved, for example, by promoting the development of breakthrough technologies and new market-creating products, rather than only supporting labor-saving automation and supply chain optimization. Future research could further explore policy implications by incorporating these findings into an endogenous growth framework, enabling policy simulations.

A key contribution of this study lies in its methodological approach. Prior research has been constrained by the absence of panel data that jointly tracks annual innovation implementation and firm-level financial information, making it difficult to assess how time-varying firm and industry characteristics influence innovation. By linking these datasets, we overcome data limitations that have hindered previous studies. Furthermore, our method enhances causal inference by leveraging IPW, a widely used technique in the causal inference literature, to control for a broader range of confounding variables than prior studies that rely solely on innovation surveys. These methodological advancements provide a foundation for future research seeking to explore the dynamic effects of innovation while addressing the inherent challenges of innovation survey data structures.

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Research data for this article

This study used microdata from the Japanese National Survey of Innovation, provided by the Ministry of Education, Culture, Sports, Science and Technology, and the Basic Survey of Japanese Business Structure and Activities, provided by the Ministry of Economy, Trade and Industry.