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

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Abstract

The invention of new goods or services, called product innovation, and improvements in production processes, called process innovation, can have distinct impacts on firm performance. By integrating firm-level innovation survey data with financial panel data in Japan, 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. Second, higher market growth stimulates product innovation, which, in turn, contributes to growth in firm sales and employment over several years. In contrast, no such patterns are observed for process innovation. These results suggest that there may be a positive feedback loop between product innovation and firm growth.

Keywords: Economic Growth; Productivity; Product Innovation; Process Innovation

JEL classification: 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 forms of innovation, product and process innovations represent two distinct channels through which firms can enhance their performance. Product innovation—introducing new goods or services to the market—can stimulate demand and expand a firm's scale. Process innovation—improving production methods or business operations—typically aims to increase efficiency and reduce costs.

While the conceptual distinction between the two is well understood, much remains unknown about how these differences translate into macroeconomic outcomes.[1] In particular, the relationship between firms' innovation decisions, their performance, and broader macroeconomic growth has yet to be fully explored. Most empirical studies are severely constrained by data derived from repeated cross-sectional surveys—typically conducted only every few years. This poses two critical limitations for economic analysis. First, the data's static nature fails to capture the core economic reality that innovation effects are dynamic and unfold over the medium term (e.g., through learning-by-doing or market penetration delays). Second, relying on such data makes it impossible to account for the unobserved pre-treatment trends which inevitably lead to selection bias, thereby obfuscating the rigorously identified causal effect of innovation. Consequently, existing static structural models, such as the CDM framework (Crépon, Duguet, and Mairesse, 1998), have been unable to rigorously establish the dynamic chain linking innovation choice, firm characteristics, and subsequent performance.

This paper resolves these critical, long-standing empirical challenges by constructing a novel longitudinal panel and applying state-of-the-art causal inference techniques. We integrate firm-level innovation survey data with consistent firm-level financial statements. This structure is essential to track the same firms over time, enabling a robust analysis of dynamic effects, a dimension previously unavailable. For reliable causal identification, we employ the doubly robust difference-in-differences (DR-DiD) estimator (Sant'Anna and Zhao, 2020; Roth et al., 2023). This powerful framework explicitly accounts for selection bias and adjusts for unobserved pre-treatment trend differences, delivering rigorously identified estimates of the dynamic average treatment effect on the treated (ATT).

[1] Previous empirical studies have demonstrated the heterogeneous effects of product and process innovations on firm performance, such as Griffith *et al*. (2006), Hall, Lotti, and Mairesse (2008), and Harrison *et al*. (2014). However, these studies primarily focus on micro-level performance from a business management perspective, with limited attention given to the broader macroeconomic implications.

Our analysis yields three central, interconnected findings that establish a dynamic causal link between market conditions, innovation choice, and firm growth. First, we document a structural, broad-based shift toward process innovation across nearly all industries and firm sizes in Japan. Second, we confirm that moderate competition acts as a key determinant, fostering both product and process innovation. Third, and most importantly, we demonstrate that market growth stimulates product innovation, which, in turn, drives sustained increases in sales and employment over the medium term. In sharp contrast, process innovation does not generate comparable dynamic effects on firm expansion.

The empirical foundation of this study is a unique panel dataset constructed by integrating the Japan National Innovation Survey (J-NIS) with detailed firm-level financial statements (Basic Survey of Japanese Business Structure and Activities, BSJBSA). This matching process is crucial because it links detailed innovation activities with consistent longitudinal data on performance, overcoming the key limitation of prior cross-sectional research. By following firms longitudinally, our dataset captures both the determinants and the dynamic consequences of product and process innovations. The matched structure further allows us to control for pre-existing firm trends and industry environments, thereby supporting the plausibility of conditional parallel trends and enabling the estimation of causal effects.

Japan provides a particularly valuable context for this analysis, serving as an essential case study for mature, advanced economies facing prolonged periods of low growth. Existing policy debates (e.g., Yoshikawa, Ando, and Miyagawa, 2013; Fukunaga et al., 2024) posit that in such environments, sustained growth hinges on demand-creating product innovation, rather than marginal improvements from process optimization. This study provides the first rigorous empirical evidence to test this fundamental hypothesis by causally examining how market conditions shape the two types of innovation and their subsequent growth effects within this critical context.

To elaborate on our first finding, we document a broad, structural shift toward efficiency, as evidenced by the rising prevalence of process innovation in Japan. Comparing two time points (early 2000s to early 2020s), we observe a notable increase in the share of firms implementing only process innovation, a trend evident across industries. A cross-country comparison reveals that Japan exhibits a particularly strong shift in this direction. Time-series analysis further confirms that, while the overall rate of innovation remains stable, the proportion of firms engaging in process-only innovation has consistently risen over time across industries and firm sizes.

Our second finding highlights the contrasting determinants of the two innovation types. Moderate competition is confirmed as a common determinant, fostering both product and process innovation, aligning with theoretical predictions and empirical evidence (Aghion et al., 2005; Igami and Uetake, 2020). This relationship remains robust even after controlling for a wider range of firm characteristics—such as employment growth and industry-level sales growth—as well as financial variables like leverage and borrowing costs. Among these factors, competition stands out as the primary driver. The inclusion of an extensive set of pre-treatment, time-varying firm-level and external environmental variables in our estimation strategy allows us to credibly establish this finding against a complex backdrop.

Our third, and most significant, finding establishes the critical dynamic feedback loop: market growth stimulates product innovation, which causally drives sustained firm expansion. Specifically, firms experiencing faster industry-level sales growth (market growth) are significantly more likely to implement product innovation and subsequently observe a lasting increase in sales and employment over the medium term. Conversely, the same stimulus-and-effect relationship is not observed for process innovation, which does not generate comparable medium-term effects on firm expansion. The finding that the growth effects of product innovation unfold gradually supports the notion that the impact of innovation is dynamic rather than immediate. This dynamic perspective is supported by literature suggesting that the benefits of innovation accumulate over time, such as through learning-by-doing (Mohnen and Hall, 2013), temporary disruption during product life cycles (Roper, Du, and Love, 2008), and complementarities between product and process innovations (Berlingieri et al., 2025).By emphasizing this dynamic effect, our study offers a potential reconciliation for the inconsistent findings that have emerged across prior empirical studies of innovation (Morris, 2018).

These findings carry significant policy implications regarding the challenges faced by mature economies. Given our causal result that high market growth is the primary stimulus for the dynamic channel of growth (product innovation), the observed structural shift toward process innovation in Japan may be a consequence of prolonged low market growth. Our results suggest that a lack of market vitality may have hindered active product innovation, leading firms to rationally redirect their investment capacity toward process innovation—a strategic choice that, while individually beneficial, lacks the capacity to stimulate economy-wide expansion.

Our paper is most closely related to the large body of empirical research that examines the effects of innovation on firm performance.[2] Early contributions, centered on the seminal CDM model (Crépon, Duguet, and Mairesse, 1998), demonstrated positive effects on firm productivity. Subsequent work has built on this foundation by exploring the differential effects of heterogeneous innovations and the impacts on various outcomes such as employment and productivity (Griffith et al., 2006; Hall, Lotti, and Mairesse, 2008; Harrison et al., 2014; Baumann and Kritikos, 2016; Aboal and Tacsir, 2018; Segarra-Blasco, Teruel, and Cattaruzzo, 2022). These studies, however, were often constrained by repeated cross-sectional surveys that lacked the necessary longitudinal firm-level financial data and precluded the application of methods such as pre-treatment trend validation. By integrating innovation survey data with firm-level financial panels, our study addresses these long-standing empirical challenges, presenting the dynamic and medium-term effects of innovation after explicitly adjusting for pre-treatment trend differences.

Our paper is also closely related to the broader, modern literature that examines how firm behavior and external conditions causally affect firm performance using advanced causal inference methods. Recent studies in related fields have successfully applied causal frameworks—such as staggered DiD, IV, and matching estimators—to firm investment decisions in R&D (Arora, Belenzon, and Sheer, 2021; Zhang et al., 2025), automation and robotics adoption (Graetz and Michaels, 2018; Bonfiglioli et al., 2024; Koch, Manuylov, and Smolka, 2021; Aghion et al., 2023; Adachi, Kawaguchi, and Saito, 2024), foreign direct investment (Desai, Foley, and Forbes, 2008), and mergers and acquisitions (Bertrand, 2009; Szücs, 2014; Ashenfelter and Hosken, 2010; Ito and Miyakawa, 2025). These prior papers share a common emphasis on causal identification supported by rich panel data. In contrast, innovation research has historically been constrained by the data limitations discussed above. By addressing these data challenges, we extend the application of these powerful modern causal inference methods—specifically DR-DiD—to the domain of innovation, offering new, rigorously identified insights into the effects of innovation on firm growth.

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.

[2] For a detailed survey of empirical research on innovation, see Mairesse, Mohnen, and Notten (2025).

2 Data

The causal identification of innovation determinants and dynamic effects necessitates a unique dataset that links firms' discrete innovation choices to their sustained, medium-term performance trajectories. To address the fundamental limitations of prior cross-sectional studies, we construct a novel longitudinal panel dataset by integrating two distinct, publicly available, firm-level data sources in Japan.

2.1 Data sources

Our empirical foundation is built upon the integration of two key Japanese firm-level data sources. The first is the Japan National Innovation Survey (J-NIS), administered by the Ministry of Education, Culture, Sports, Science and Technology (MEXT). This survey provides comprehensive and detailed information on firm-level innovation activities, including the implementation of product, process, organizational, and marketing innovations, alongside R&D expenditure and cooperation networks. The J-NIS adheres to the international standards set by the Oslo Manual (OECD and Eurostat, 2018), ensuring that the definition of product and process innovation is consistent with global research and remains reliable across survey waves.

The second source is the Basic Survey of Japanese Business Structure and Activities (BSJBSA), administered by the Ministry of Economy, Trade and Industry (METI). The BSJBSA provides consistent, longitudinal information, including detailed financial statements (BS/PL), employment data, and capital investment metrics, over a two-decade period. Prior innovation research has been severely constrained because innovation surveys like J-NIS are typically conducted only as repeated cross-sections, precluding the longitudinal tracking of firms over time.

2.2 Matching strategy and panel construction

The core contribution of our data lies in the successful, high-precision matching of these two datasets using unique firm identifiers. Specifically, the National Tax Agency (NTA) ID is available for the latter part of our sample (post-2018 J-NIS waves). This enables straightforward initial matching, and crucially, allows us to leverage the BSJBSA's unique longitudinal firm ID to track firms backward in time, maximizing the panel's depth.

For the earlier waves, however, the construction of our long panel requires an intensive, best-effort matching strategy, utilizing imperfect and time-varying identifiers such as firm name and address. By overcoming this technical and data limitation, our matched panel is essential for two reasons: (1) It links the decision to innovate to subsequent medium-term performance, enabling the tracking of dynamic effects. (2) It allows us to explicitly measure and control for unobserved pre-treatment trends and firm-specific characteristics, which is vital for applying the DR-DiD estimator and mitigating selection bias. The resulting panel covers the period from the early 2000s to the early 2020s, capturing a critical period of structural change in a mature economy.

The final estimation sample comprises approximately 41,200 firm-year observations spanning 20 years of the panel (2003-2022). As detailed in Table 1, the matched sample includes between 1,602 and 4,095 firms per J-NIS survey wave, resulting in this large number of annual observations. The matched sample is characterized by the BSJBSA's underlying coverage restrictions (minimum thresholds for capital and employment), meaning it predominantly features established medium- to large-sized firms in manufacturing and non-manufacturing sectors.

3 Methodology

Our empirical strategy is structured to first define the innovation indicators (Section 3.1), analyze the determinants of innovation implementation (Section 3.2), and then to estimate the dynamic causal effects of innovation on firm performance (Sections 3.3 and 3.4). This structured approach is crucial as the analysis of the determinants of innovation implementation helps us find the relevant covariates required for robust causal inference on the dynamic effects of innovation on firm performance.

3.1 Innovation indicators and definitions

The core indicators for our study are based on the J-NIS survey responses. The Product Innovation Rate ($R_{prod,t}$) and Process Innovation Rate ($R_{proc,t}$) are defined as the number of firms that implemented at least one product or process innovation ($N_{prod,t}$ or $N_{proc,t}$) during the preceding three-year period (from $t-3$ to $t-1$), divided by the total number of firms surveyed (N_t) in year t:

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

(Table 1) Sample sizes from the J-NIS and BSJBSA and the final matched sample

Year	BSJBSA, METI	J-NIS, MEXT	Matched Sample
2003	27,545	9,257	2,417
2004	27,055		2,417
2005	28,340		2,417
2006	27,677		2,417
2007	27,917		2,417
2008	29,080		2,417
2009	29,355	4,579	1,722
2010	29,096		1,722
2011	29,570		1,722
2012	30,647		1,722
2013	30,584	7,034	1,614
2014	30,217		1,614
2015	30,180	12,526	1,602
2016	30,231		1,602
2017	30,151		1,602
2018	29,530	9,439	2,366
2019	29,780		2,366
2020	29,295	12,534	3,929
2021	29,574		3,929
2022	34,056	13,181	4,095

Notes: This table summarizes the number of firms in each survey year for the J-NIS and BSJBSA, as well as the number of firms successfully matched across the two surveys using firm names and identifiers.

Furthermore, we define the Process-Only Innovation Ratio ($R_{proc-only,t}$) as the number of firms that implemented only process innovation ($N_{proc-only,t}$) divided by the total number of firms that implemented at least one type of innovation ($N_{innov,t}$).

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

This metric is essential for our descriptive analysis, as it precisely tracks the structural shift toward efficiency-driven activities. The Product-Only Innovation Ratio ($R_{prod-only,t}$) can be defined similarly.

3.2 Modeling innovation determinants

Following the established tradition in innovation research, we first examine how firm characteristics and the surrounding economic environment relate to the likelihood of innovation implementation. This analysis serves two critical purposes: to identify key drivers of innovation (the "determinants" finding) and, more importantly, to identify the pre-treatment covariates necessary for constructing the propensity score in the subsequent causal analysis.

It is important to note the distinction between innovation choice (or effort) and innovation implementation. While the former reflects the firm's strategic commitment (e.g., R&D expenditure) and their facing barriers such as financial constraints, the latter depends on the eventual success of that effort and is susceptible to different factors, notably market barriers. We estimate a probit model focusing on product-only or process-only innovation to capture distinct innovation types at the implementation stage.[3]

The estimation takes the following form:

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

where $Innov_{x,i,t} = 1$ is a dummy variable indicating that firm i implemented only innovation type $x \in \{Product, Process\}$ during the three-year period from year t to $t+2$. $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. The explanatory variables include market environment factors such as $Comp_{i,t}$ (market competition intensity) and $Growth_{j(i),t-1}$ (sales growth rate for industry group j to which firm i belongs). Industries are based on the Major Groups (two-digit codes) of the Japanese Standard Industrial Classification (JSIC), resulting in 89 distinct industry groups in our sample. The vector $\boldsymbol{Z}_{i,t-1}$ includes an extensive set of pre-treatment, time-varying firm-level financial characteristics—such as log Sales, R&D expenditure per employee, interest rate (calculated as interest payments divided by total debt), and leverage ratio (calculated as total debt divided by total assets)—all crucial for mitigating selection bias. The inclusion of year (α_t), industry ($\lambda_{j(i)}$), and regional (δ_r) fixed effects accounts for unobserved time-invariant and time-specific heterogeneity. We use prefecture-level

[3] We discuss the different roles played by R&D and financial variables in innovation effort and innovation implementation in detail in Section 4.2.

variation for regions, controlling for 47 classifications.

3.3 Estimating dynamic causal effects

The core of our study lies in quantifying the dynamic causal impact of innovation over the medium term. Given the data constraint that innovation status is observed only at discrete survey waves, we estimate the Average Treatment Effect on the Treated (ATT) at multiple time horizons (h) following the innovation implementation (treatment).

The ATT for innovation type x at time horizon h is defined as:

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

where $Y_{i,h}(1)$ and $Y_{i,h}(0)$ represent the potential outcomes (e.g., employment growth, sales growth, real labor productivity, and markup changes) with and without innovation, respectively, h years after the innovation period. By estimating the ATT across several horizons, we directly address the limitations of static models and observe the full unfolding of innovation benefits over time.

3.4 Doubly robust difference-in-differences and causal identification

To ensure the causal validity of these dynamic estimates, we employ the Doubly Robust Difference-in-Differences (DR-DiD) estimator (Sant'Anna and Zhao, 2020; Roth et al., 2023). This choice is central to our identification strategy and positions our work within the frontier of causal inference methods. Critically, given the nature of the J-NIS data (repeated cross-sections that do not continuously track a firm's precise innovation adoption history), we cannot employ the Staggered DiD estimators designed for complex treatment timing (e.g., Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Therefore, the DR-DiD estimator is interpreted here as primarily relying on the Selection on Observables assumption (i.e., conditional independence) rather than the strict, untestable parallel trends assumption of conventional DiD. This interpretation is necessary given our data environment and aligns our approach with recent methodological literature that emphasizes robust estimation under strong selection.

The estimator DR-DiD ATT is constructed using the following components, incorporating the non-treated outcomes adjusted by both propensity score weighting and outcome regression:

$$\widehat{ATT}_{x,h}^{DR} = \frac{1}{N_{1,h}}\sum_{i\in T} y_{i,h} - \left(\frac{1}{N_{1,h}}\sum_{i\in T}\hat{\mu}_{0,h}(X_i) + \frac{1}{N_{1,h}}\sum_{i\notin T}\left[\frac{\hat{e}_{i,t}}{1-\hat{e}_{i,t}}\left(y_{i,h} - \hat{\mu}_{0,h}(X_i)\right)\right]\right) \qquad (5)$$

where $N_{1,h}$ is the number of treated firms, T denotes the set of treated firms, and $\hat{e}_{i,t}$ is the estimated propensity score. The estimated outcome regression model ($\hat{\mu}_{0,h}$) is derived from the expected outcome of the control group given the pre-treatment covariates ($\boldsymbol{X}_i$), specifically: $\hat{\mu}_0(\boldsymbol{X}_i) = E\left[Y_{i,h}\middle|\boldsymbol{X}_i, i \notin T\right]$. Confidence intervals for the estimated ATTs are constructed using a nonparametric bootstrap method. The resulting rigorous identification framework represents a significant methodological advancement over traditional innovation studies. The covariate set $\boldsymbol{X}_i$ used here is identical to the set of pre-treatment covariates defined in the propensity score model (Section 3.2).

The DR-DiD estimator provides consistent estimates of the ATT if either the propensity score model or the outcome regression model for the comparison group is correctly specified, but not necessarily both. This double robustness provides critical protection against potential model misspecification when controlling for observed time-varying confounders.

Furthermore, we leverage the longitudinal structure of our matched panel to empirically assess the plausibility of the Conditional Parallel Trends (CPT) assumption as an empirical test of the quality of the Selection on Observables assumption. We examine the dynamic ATT estimates during the pre-treatment period ($h < 0$). Crucially, using covariates available solely in the J-NIS survey, the differential pre-trends are highly significant, leading to biased causal effects (Appendix 1). The absence of statistically significant differential pre-trends in the outcome variables—after controlling for the extensive set of time-varying covariates provided by the BSJBSA—proves a compelling empirical evidence supporting the validity of our Selection on Observables assumption in this setting.

4 Empirical results

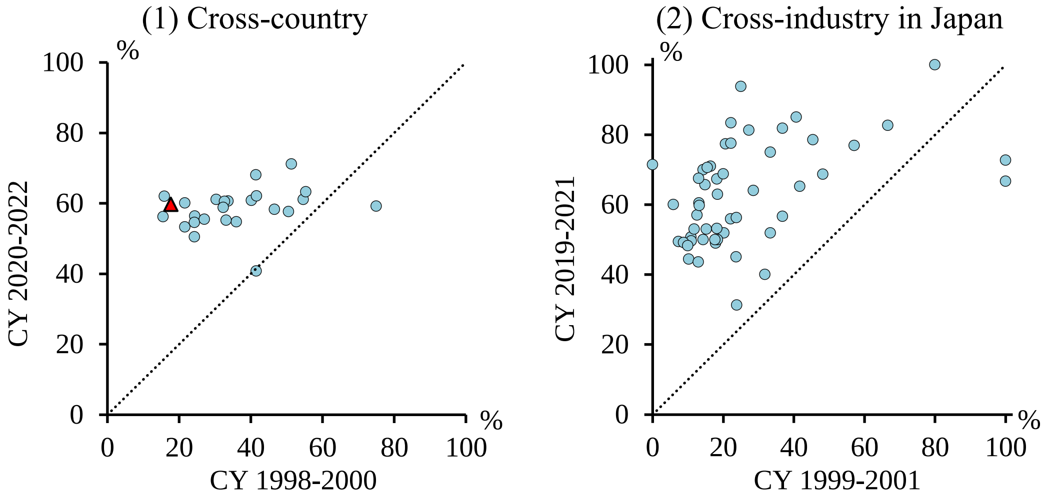
This section presents the core empirical results of our study, documenting the structural shift in innovation activity, analyzing the determinants of innovation choice, and finally, quantifying the dynamic causal effects of each innovation type on firm performance.

4.1 Structural shift and descriptive evidence on innovation activities

We begin by documenting the long-term trends and cross-sectional patterns of product and process innovation that motivate our dynamic causal analysis. A key stylized fact is the structural, broad-based shift toward process innovation across Japanese firms over the past two decades. This re-orientation toward efficiency-driven investments, occurring in a mature, low-growth context, forms the central puzzle that our causal analysis seeks to resolve and provides the critical policy context for our findings. Unless otherwise noted, the analysis focuses on the cross-sectional distribution and time-series trends using the multi-wave J-NIS data.

Figure 1 shows the prevalence of innovation across countries using a two-period comparison (e.g., comparing the early 2000s to the early 2020s). This comparison demonstrates that the increasing ratio of process innovation is pervasive across broad industries and firm sizes and is particularly pronounced in Japan relative to European peers.

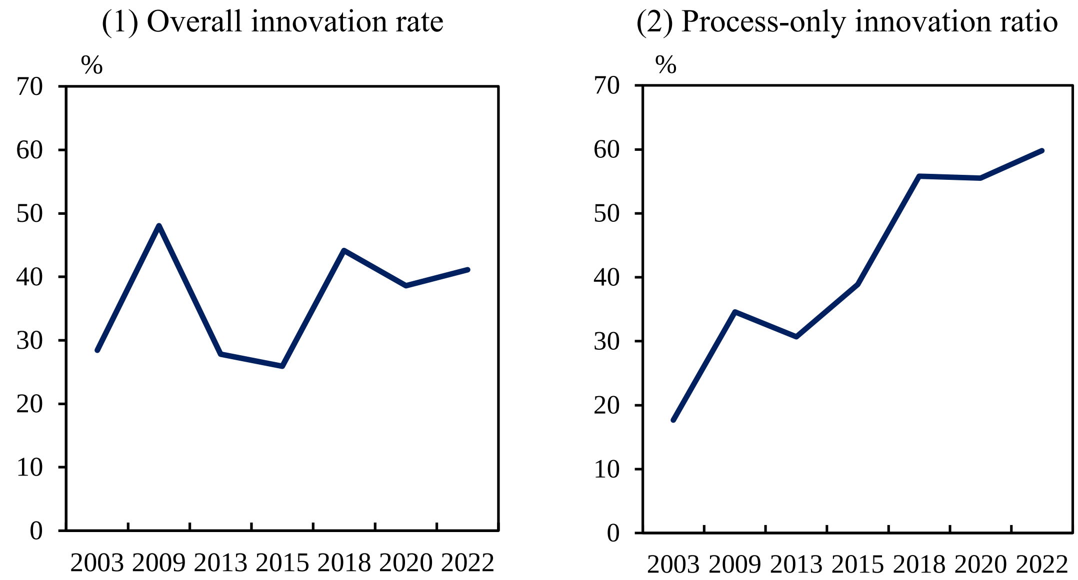
(Figure 1) Process innovation ratio across countries and industries



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. Data for European countries are from the Community Innovation Survey (CIS) provided by Eurostat, while data for Japan are from the J-NIS provided by MEXT.

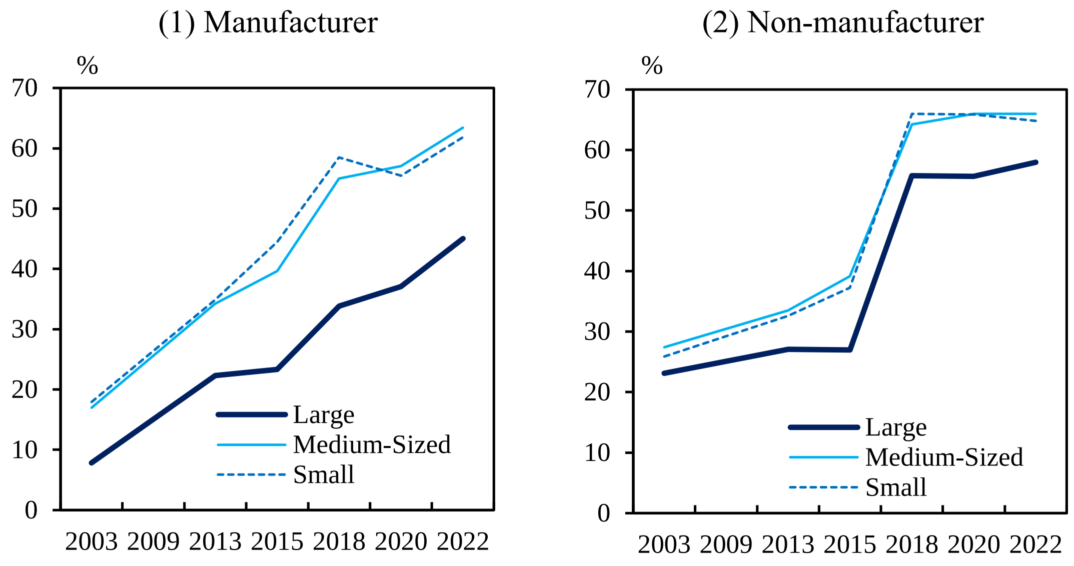
Next, to confirm the long-term consistency and durability of this structural shift, we examine the granular time-series trends within Japan. Figure 2 shows that while the overall innovation rate has remained stable, the proportion of innovating firms engaging in process-only innovation has risen significantly and consistently throughout the observation period. Furthermore, Figure 3 confirms the robustness of this long-term trend, showing it is evident across major industry groupings (manufacturing and non-manufacturing) and different firm sizes. While the process-only innovation ratio varies by firm size (e.g., larger firms are generally less likely to report only process innovation), the increasing trend is universally observed across both manufacturing and non-manufacturing sectors, supporting the notion of a fundamental, economy-wide structural change. We note a sharp increase in the non-manufacturing sector's process-only ratio after the 2018 survey, likely reflecting a questionnaire change that expanded the definition of process innovation; however, the persistent upward trend remains robust even accounting for this discontinuity.

(Figure 2) Innovation and process-only rates



Notes: Panel (1) shows the share of firms that implemented either product or process innovation. The x-axis indicates the survey year, with each survey referring to innovation activities conducted during the preceding three-year period. Panel (2) shows the share of firms that implemented only process innovation among those that implemented either type of innovation.

(Figure 3) Process-only innovation ratio by industry and firm size



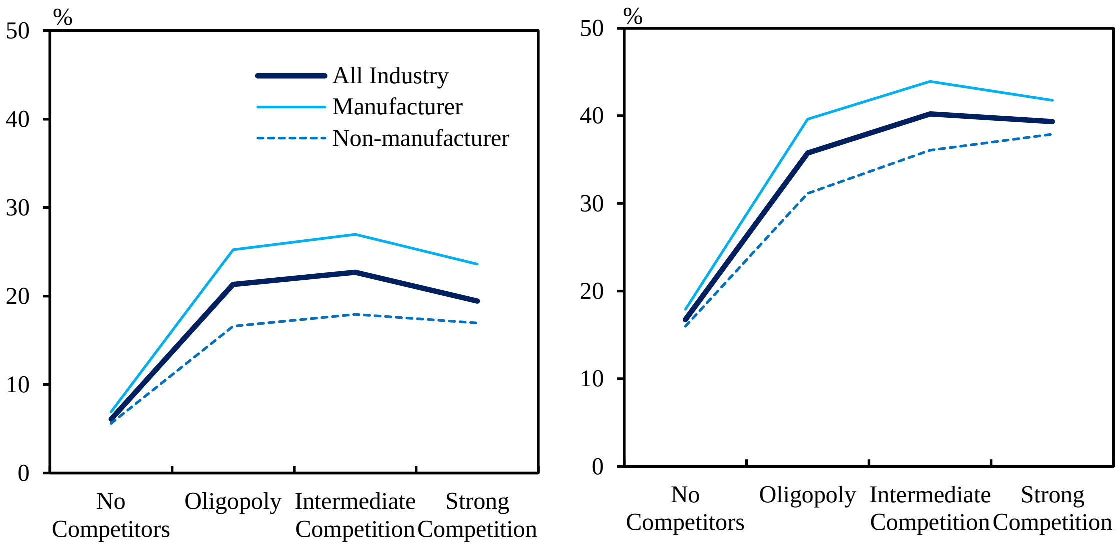
Notes: Firm size is categorized into three groups based on the number of employees: fewer than 50, 50–249, and 250 or more.

Furthermore, we confirm that the likelihood of innovation is systematically related to the competitive environment (Figure 4). Product innovation displays an inverted-U relationship with competitive intensity, peaking under intermediate competition before declining under excessive competition. This result is consistent with the leading theoretical framework on product innovation incentives, as established in the seminal work by Aghion et al. (2005).[4] In contrast, process innovation exhibits a saturation pattern, suggesting that its incentive structure is less sensitive to the highest levels of competition. This saturation pattern is strikingly consistent with the established findings, based on R&D investment probability, that specifically distinguish the response to competition (Igami and Uetake, 2020).

[4] Hashmi (2013) finds a mildly negative relationship between competition and innovation in the U.S. data, contrasting the inverted-U result from the U.K. data, and reconciles this difference by modifying the theoretical model to incorporate varying degrees of technological neck-and-neckness. For a broad survey of the competition-innovation debate, see Griffith and Van Reenen (2022).

(Figure 4) Product and process innovation rates by competition level

(1) Product innovation rate (2) Process innovation rate

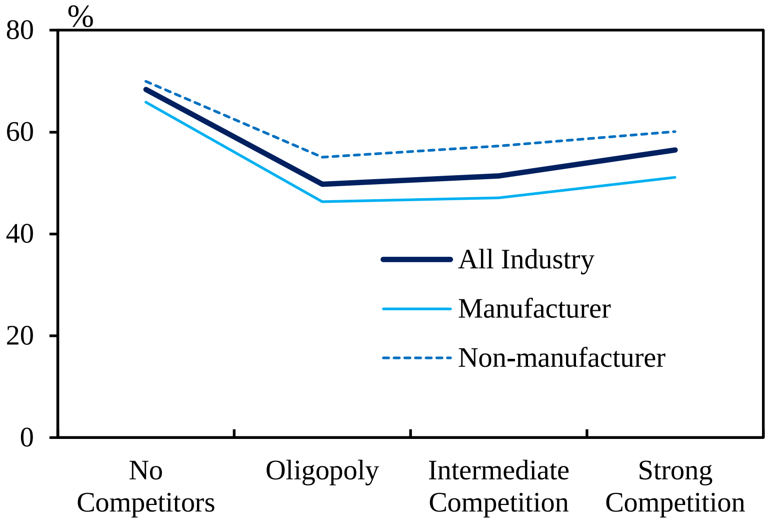


Notes: Competition categories on the horizontal axis are defined by the number of competitors as follows: no competitors (0), oligopoly (1–5), intermediate competition (6–14), and strong competition (15 or more). For the 2009 survey, the thresholds used were slightly different: 1–4 for oligopoly, 5–20 for intermediate competition, and 21 or more for strong competition. The values are based on pooled data from four survey years: 2009, 2018, 2020, and 2022.

Expanding on this, Figure 5 shows that the process-only innovation ratio follows a U-shaped pattern with respect to competitive conditions. This inverse relationship highlights the resource allocation shift: while extreme competitive conditions (both monopolistic and intense) suppress overall innovation likelihood (Figure 4), they simultaneously incentivize a relative re-orientation of resources toward pure process innovation. This suggests that when firms choose to innovate in such environments, they overwhelmingly favor defensive, cost-saving process investments over demand-creating product investments.

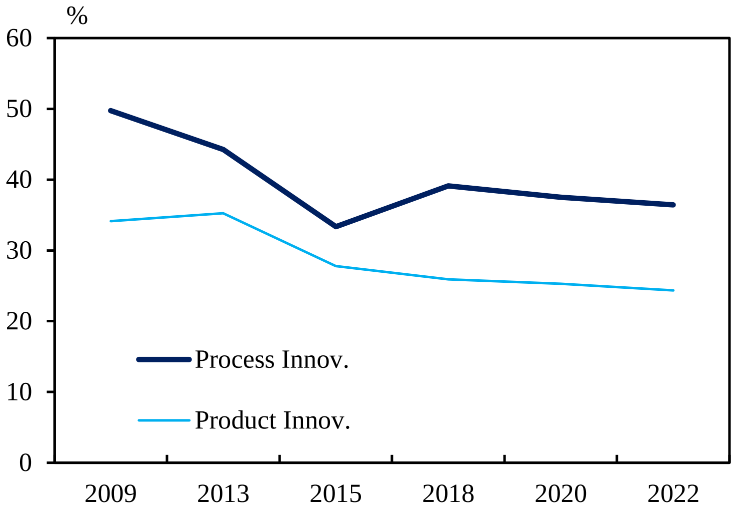
To capture the dynamic reality of innovation, we also document that innovation status is not permanent; a significant proportion of firms change their innovation status between survey waves (Figure 6). This observation supports the identification strategy of our dynamic analysis, as innovation decisions are not solely determined by fixed firm-specific factors but also respond to time-varying external conditions.

(Figure 5) Process-only innovation ratio by competition level



Notes: See Figure 4 for the definitions of competition categories.

(Figure 6) Share of firms that changed innovation status across surveys



Notes: This figure illustrates the share of firms that gave different responses to innovation implementation questions between two consecutive surveys. Each x-axis label indicates the survey year being compared with the previous survey.

4.2 Determinants of innovation implementation

We next examine the factors associated with a firm's decision to implement product-only or process-only innovation, effectively modeling the propensity score for the DR-DiD estimator using the estimation equation (3). This analysis yields crucial, contrasting insights into the selection mechanism that precedes the dynamic effects documented in the next subsection.

The most significant distinction between the two innovation types lies in the impact of industry-level sales growth (a proxy for market demand growth). Specifically, industry sales growth is positively and significantly associated with product-only innovation (Table 2). For product innovation, a one-percentage-point increase in industry sales growth raises the marginal probability of implementation by approximately 0.2 percentage points, suggesting that firms perceive and act on greater opportunities for demand capture and market expansion in faster-growing industries, aligning incentives for demand-creating product investments. In stark contrast, industry sales growth is not significantly associated with the likelihood of process-only innovation (Table 3). This lack of a positive growth-incentive signal highlights the defensive, efficiency-focused nature of process innovation, which proceeds regardless of—or perhaps in response to—low market growth.

A shared and powerful determinant, however, is the intensity of competition. We confirm that moderate competition (e.g., 1-5 competitors), compared to monopolistic conditions (no competitors), is strongly associated with both product and process innovation (Tables 2 and 3). Moving from no competitors to this moderate level of competition is associated with an increase in innovation probability of approximately 23 percentage points for product innovation and 14 percentage points for process innovation. This aligns with the consensus that some level of competitive pressure is necessary to incentivize innovation. The results further show that the decrease in the probability of implementation in the group with the highest competitive intensity, relative to the moderate competition group, is more pronounced for product innovation than for process innovation. Specifically, the marginal effect for product innovation drops from approximately 24 percentage points to 19 percentage points, whereas for process innovation, the drop is smaller, going from approximately 15 percentage points to 14 percentage points, although the difference between the two competitive groups is not statistically significant for both types of innovation.

(Table 2) Probit estimation: determinants of product-only innovation

	(1)	(2)	(3)	(4)
No. of Competitors: 1-5	0.2327***	0.2301***	0.2277***	0.2287***
	(0.0643)	(0.0653)	(0.0599)	(0.0626)
No. of Competitors: 6-14	0.2426***	0.2409***	0.2376***	0.2395***
	(0.0653)	(0.0711)	(0.0606)	(0.0676)
No. of Competitors: 15-	0.1900**	0.1989**	0.1860**	0.1977**
	(0.0762)	(0.0836)	(0.0723)	(0.0812)
Industry Growth Rate (past 3 years)	0.0018**	0.0018**	0.0018**	0.0019**
	(0.0008)	(0.0009)	(0.0008)	(0.0009)
Employment Growth Rate (past 5 years)	-0.0003	0.0009	-0.0002	0.0009
	(0.0006)	(0.0008)	(0.0005)	(0.0008)
log(Age)		0.0008**		0.0008**
		(0.0003)		(0.0003)
log(Sales)*1,000	0.0025***	0.0019***	0.0025***	0.0019***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(LP) *100		-0.2819		-0.3174
		(0.0023)		(0.0025)
log(R&D Expenditure /Employee) *100		0.0222***		0.0219***
		(0.0000)		(0.0000)
Interest Rate			0.0110*	0.0009
			(0.0056)	(0.0080)
Levarage Ratio			-0.0009***	-0.0004**
			(0.0002)	(0.0002)
Fixed Effects				
Industries	Y	Y	Y	Y
Years	Y	Y	Y	Y
Regions	Y	Y	Y	Y
N	7,284	7,281	7,284	7,281
AIC	6,482	6,285	6,478	6,288
AUC	0.72	0.75	0.72	0.75

Notes: This table reports estimation results from a probit model using four different sets of covariates. The reported coefficients are marginal effects. Robust standard errors clustered at the industry and prefecture levels are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

(Table 3) Probit estimation: determinants of process-only innovation

	(1)	(2)	(3)	(4)
No. of Competitors: 1-5	0.1431***	0.1417***	0.1442***	0.1424***
	(0.0405)	(0.0411)	(0.0431)	(0.0426)
No. of Competitors: 6-14	0.1512***	0.1491***	0.1526***	0.1499***
	(0.0304)	(0.0324)	(0.0327)	(0.0336)
No. of Competitors: 15-	0.1378***	0.1387***	0.1391***	0.1397***
	(0.0330)	(0.0350)	(0.0347)	(0.0358)
Industry Growth Rate (past 3 years)	-0.0022	-0.0021	-0.0022	-0.0021
	(0.0019)	(0.0023)	(0.0018)	(0.0024)
Employment Growth Rate (past 5 years)	0.0025***	0.0025***	0.0024***	0.0025***
	(0.0002)	(0.0009)	(0.0002)	(0.0008)
log(Age)		-0.0001		0.0000
		(0.0002)		(0.0003)
log(Sales)*1,000	0.0016***	0.0016***	0.0015***	0.0014***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(LP) *100		-0.2169*		-0.1813
		(0.0012)		(0.0013)
log(R&D Expenditure /Employee) *100		0.0080***		0.0083***
		(0.0000)		(0.0000)
Interest Rate			-0.0212*	-0.0238
			(0.0108)	(0.0154)
Levarage Ratio			0.0005***	0.0006
			(0.0001)	(0.0004)
Fixed Effects				
Industries	Y	Y	Y	Y
Years	Y	Y	Y	Y
Regions	Y	Y	Y	Y
N	8,765	8,762	8,765	8,762
AIC	10,264	10,256	10,264	10,255
AUC	0.69	0.69	0.69	0.70

Notes: This table reports estimation results from a probit model using four different sets of covariates. The reported coefficients are marginal effects. Robust standard errors clustered at the industry and prefecture levels are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Finally, the impact of financial conditions differs markedly. For product innovation, a lower leverage ratio and higher interest rates are initially associated with greater product innovation activity (Table 2). The positive correlation with high interest rates can be seen as natural, considering that high-risk, high-reward product innovation is often linked to higher perceived risk and thus potentially higher financing costs. Furthermore, the association with a low leverage ratio suggests that firms engaging in product innovation may rely more heavily on external financing models—such as venture capital—that provide both capital and non-financial support, or they may simply maintain stronger balance sheets. However, when R&D expenditure per employee is controlled for, the significant association between low leverage and product innovation persists. This indicates that for product innovation, the firm's balance sheet structure (low leverage) has a direct, enabling effect on the innovation outcome, independent of the volume of R&D spending. In the case of direct financing, the ongoing non-financial support after funding—such as managerial guidance and strategic advice—may significantly increase the likelihood of successful product innovation. The positive association with the interest rate disappears when R&D expenditure is controlled for, indicating that high interest rates primarily reflect the risk of the R&D input itself.[5]

In contrast, process innovation shows a positive association with the leverage ratio (Table 3). When R&D expenditure per employee is explicitly controlled for, the significant effects of both the leverage ratio and the interest rate on process innovation disappear. This result strongly underscores the importance of financial accessibility as an indirect factor for process innovation: it operates primarily by enabling innovation efforts (R&D spending), rather than by directly determining the technical success or failure of the innovation output itself.

4.3 Causal effects of innovation on firm performance

We now present the central finding of this paper: the quantification of the heterogeneous and dynamic causal effects of innovation. We use the Doubly Robust Difference-in-Differences (DR-DiD) estimator, which implements Equation (5), to identify the Average Treatment Effect on the Treated (ATT) at multiple time horizons following innovation adoption. This methodology explicitly addresses the long-standing empirical challenges of self-selection and unobserved pre-treatment trends.

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[5] R&D investment is heterogeneous. The Survey of Research and Development, provided by the Ministry of Internal Affairs and Communications (MIC), classifies R&D into basic, applied, and development research. It is crucial to examine how firm attributes and the external environment specifically shape the incentives for each of these research stages; thus, we conduct complementary analyses to explore these heterogeneous determinants (Appendix 2).

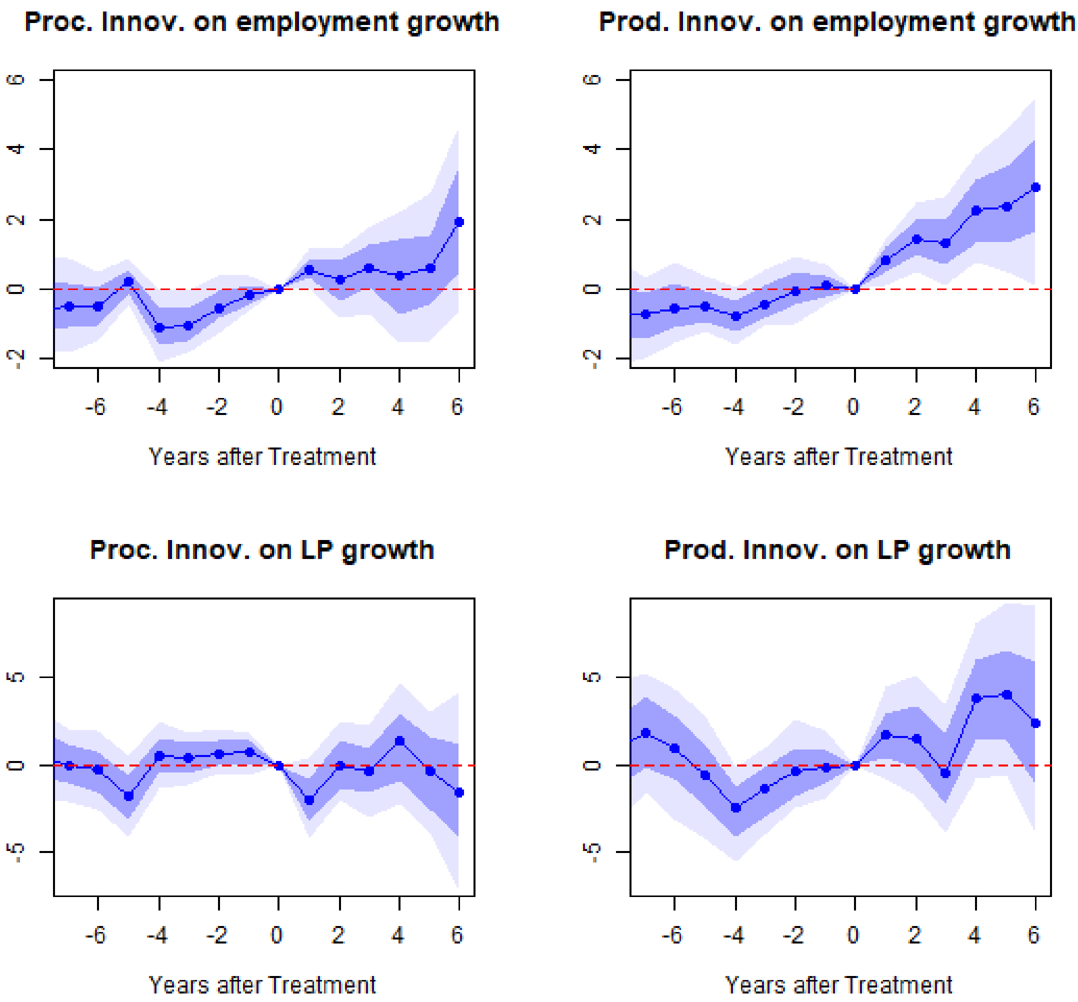
Our causal analysis establishes a clear, sustained, and economically significant dynamic feedback loop for product innovation, a pattern strikingly absent for process innovation. This effect manifests as a statistically significant and sustained positive impact on sales and employment growth over the medium term (Figures 7 and 8). Crucially, the effect unfolds gradually, supporting the mechanism that the benefits of demand-creating innovation accumulate over time through market penetration and learning, rather than manifesting immediately. Specifically, the cumulative effect of product innovation on sales reaches approximately 6% over a six-year horizon post-treatment (Figure 8). This sales expansion translates directly into a lasting increase in employment, indicating that product innovation is a robust driver of job creation and firm scaling.

In sharp contrast to this expansionary effect, process innovation (process-only), while aimed at efficiency and cost reduction, does not generate a statistically significant dynamic effect on either sales or employment at any post-treatment horizon (Figures 7 and 8). This causal finding supports the hypothesis, particularly relevant to mature economies, that purely cost-saving innovation is insufficient to stimulate medium-term firm expansion across the board. Furthermore, regarding other performance metrics, neither type of innovation yields statistically significant effects for real labor productivity (LP) growth.[6] For markup, product innovation shows a modest, temporary increase that gradually fades, consistent with the product life cycle hypothesis (Abe et al., 2016; Inokuma, Katagiri, and Sudo, 2024), while process innovation yields a consistently flat, statistically insignificant estimate.

The robustness of these causal estimates rests on the strong Selection on Observables assumption, which we adopt given the multi-wave, non-continuous nature of the J-NIS data. Relying solely on covariates available in the J-NIS survey leads to significant pre-treatment differential trends and yields biased causal effects (as documented in Appendix 1), particularly crucial for the effect of process innovation on employment. The absence of statistically significant pre-treatment ATTs—after rigorously controlling for our rich set of time-varying covariates—provides the empirical support for the validity of the Selection on Observables assumption in this setting. This rigorous approach, leveraging the DR-DiD estimator with our unique longitudinal panel, provides a significant methodological advancement over prior innovation studies, which could not credibly control for these long-term, time-varying confounders.

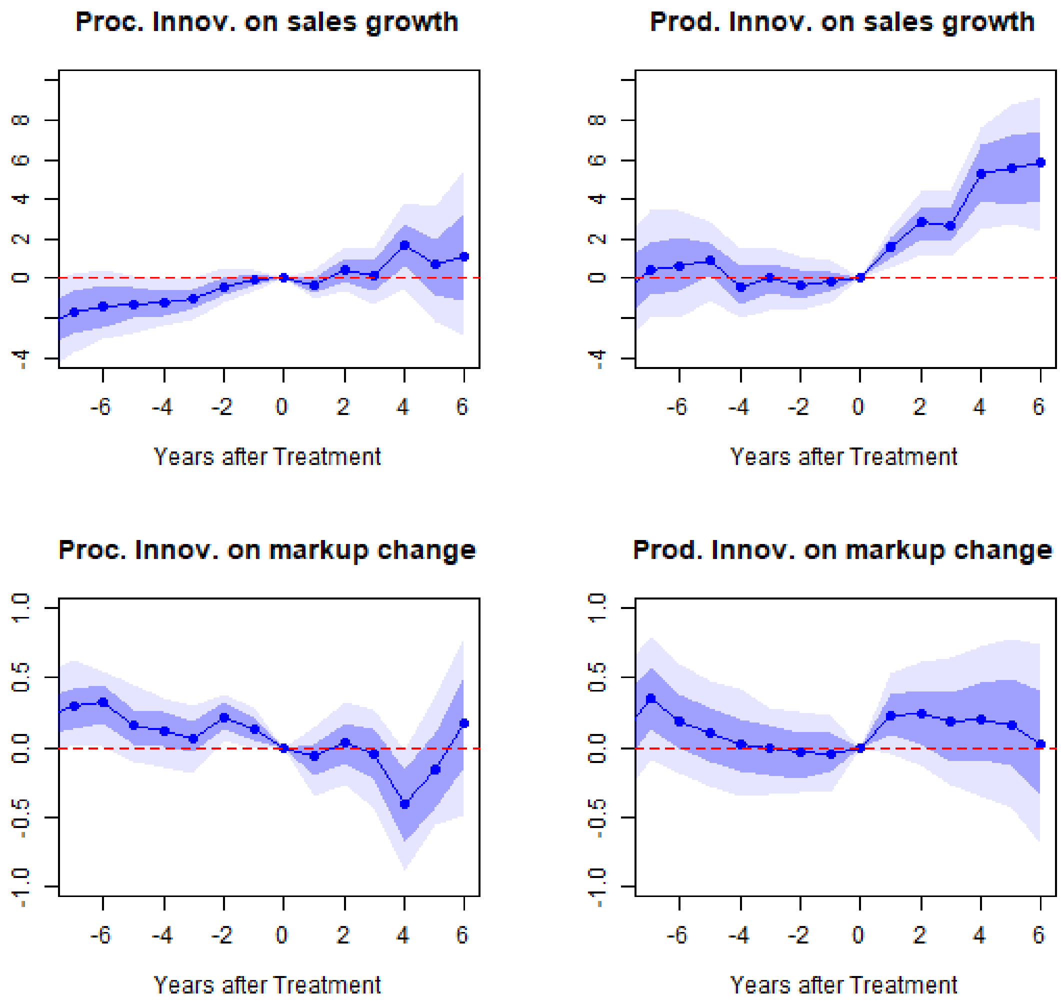
[6] In Appendix 3, we also analyze the causal effects of both types of innovation on other efficiency-related outcomes, but no significant effect was found for any of them.

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



Notes: This figure shows the estimated cumulative effects of innovation on firms' employment and labor productivity growth, based on the DR-DiD estimators to estimate the ATT. The dark and light shaded areas represent 68% and 95% confidence intervals, respectively, constructed from the percentiles of 200 bootstrap replications.

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



Notes: This figure shows the estimated cumulative effects of innovation on firms' sales growth and markup, based on the DR-DiD estimators to estimate the ATT. The dark and light shaded areas represent 68% and 95% confidence intervals, respectively, constructed from the percentiles of 200 bootstrap replications.

5 Conclusion

This study establishes a dynamic, causal foundation for understanding the heterogeneity of firm innovation and its link to medium-term economic growth, resolving long-standing empirical challenges in the literature. By integrating the Japan National Innovation Survey (J-NIS) with rich longitudinal financial data and employing the doubly robust difference-in-differences (DR-DiD) estimator, we provide rigorously identified evidence on the determinants and dynamic effects of product versus process innovation.

Our analysis yields several key findings that redefine the innovation-growth nexus. First, we document a structural, broad-based shift toward process innovation in Japan over the past two decades. Furthermore, we causally confirm that moderate competition fosters both types of innovation, though industry-level sales growth (a proxy for market demand) primarily stimulates product innovation, while it has no significant effect on process innovation. Most critically, we establish a dynamic causal feedback loop: product innovation causally drives sustained increases in firm sales and employment over the medium term. This effect unfolds gradually, supporting the notion that innovation benefits accumulate over time (e.g., through learning-by-doing and market penetration). In sharp contrast, process innovation does not generate comparable dynamic effects on firm expansion. By explicitly accounting for the timing of effects, our dynamic analysis offers a potential reconciliation for the inconsistent findings that have emerged across prior empirical studies of innovation.

These findings carry significant policy implications for advanced economies struggling with stagnant economic growth. Our core result suggests that the observed shift toward process optimization in Japan may be a rational consequence of weak market vitality, rather than its cause. While labor-saving automation and supply chain optimization (process innovation) are individually efficient, they lack the capacity to stimulate broader economic expansion. Therefore, from a policy perspective, encouraging demand-creating product innovation is essential for achieving a sustained boost to growth. This requires industrial policy that supports the development of new market-creating products and breakthrough technologies, shifting the focus away from a sole emphasis on efficiency-driven, labor-saving measures. Our analysis suggests that efforts to boost aggregate demand and market growth would be the most effective stimulus for the dynamic growth channel.

This study's construction of a unique, causally informative longitudinal dataset—linking innovation implementation to medium-term outcomes—provides a robust empirical foundation. Future research can build on this work by embedding these findings into a structural endogenous growth framework. Such research could clarify the precise mechanisms through which market environments shape innovation implementation, and how the differential contributions of product and process innovation ultimately aggregate to macroeconomic outcomes, thereby providing a basis for evaluating optimal industrial policy responses.

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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, the Basic Survey of Japanese Business Structure and Activities, provided by the Ministry of Economy, Trade and Industry, and the Survey of Research and Development, provided by the Ministry of Internal Affairs and Communications. These microdata are confidential and not publicly available.

Appendix 1. Covariate selection and pre-trend validity check

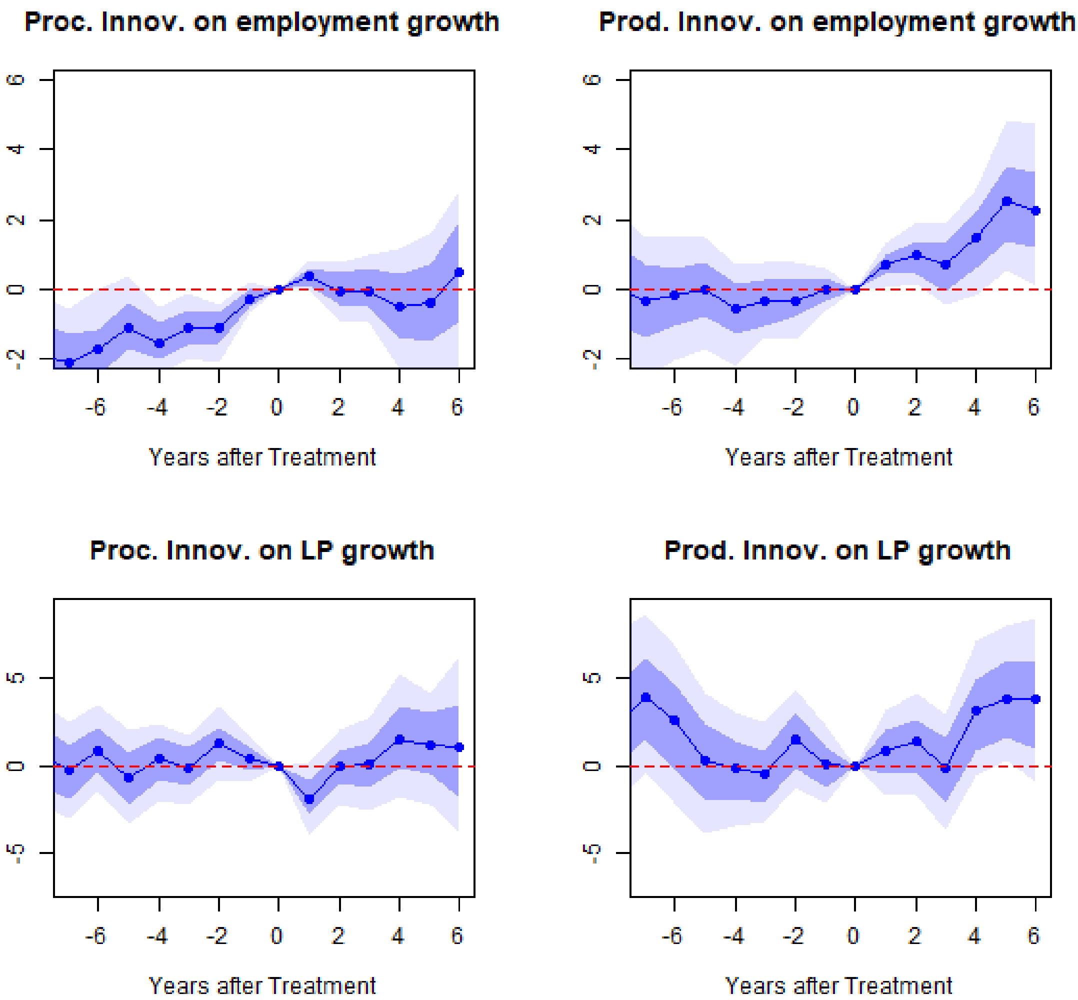
This appendix provides empirical evidence supporting our choice of a rich set of pre-treatment covariates and the credibility of the conditional parallel trends (CPT) assumption for causal identification. As discussed in Section 3.4 of the main text, our causal identification relies on the Selection on Observables assumption, whose plausibility is empirically supported by demonstrating that the pre-treatment average treatment effects on the treated (ATT) are not statistically significant after controlling for our comprehensive set of time-varying covariates. To highlight the importance of the matched panel data (BSJBSA variables) in controlling for pre-trend bias, we estimate the dynamic ATT using a limited covariate set available only in the J-NIS survey. This limited set comprises log(Sales), log(Age), and the Number of Competitors.

Figure A1, illustrates the dynamic ATT estimates for employment and labor productivity (LP) growth using only this limited covariate set. Regarding the result for process innovation on employment, the upper-left panel of Figure A1 reveals an increasing pre-trend in employment growth prior to the implementation of process innovation. This spurious positive pre-trend suggests that firms with higher pre-existing employment growth are more likely to adopt process innovation. A critical finding is that the rich covariate set successfully eliminates this significant pre-trend bias. This ensures that the pre-treatment ATTs close to zero, providing compelling empirical validation of the Selection on Observables assumption for the DR-DiD estimator in this context.

Furthermore, we assess the direction of the the post-treatment bias arising from the uncontrolled selection. The upper-left panel of Figure A1 reveals that, despite the significant positive pre-trend, the post-treatment ATTs exhibit a tendency toward negative values in the medium term (a pattern that might intuitively suggest that firms prone to process innovation tend to suppress employment after implementation)—a result inconsistent with the non-significant effect identified after comprehensive covariate control (Figure 7). This discrepancy suggests a potential downward bias when rich covariates are omitted, misrepresenting the non-significant effect and thus reinforcing the importance of incorporating detailed BSJBSA data for unbiased dynamic estimates.

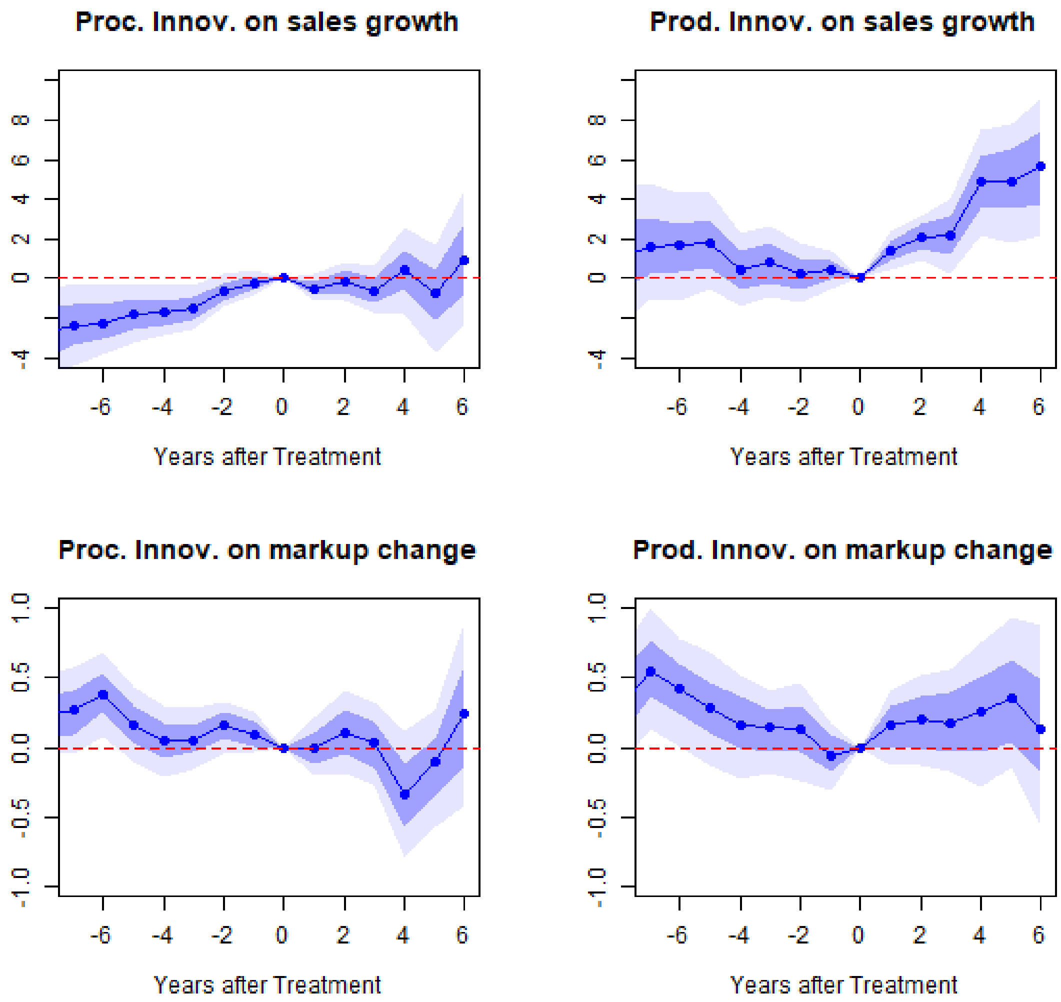
Figure A2 provides the corresponding dynamic ATT estimates for firm's sales and markup growth. The pre-treatment sales trends for process innovation (upper-left panel) exhibit a significant increasing pre-trend, similar to the employment results, indicating selection bias. Although the post-treatment effects remain non-significant, this collectively reinforces the importance of eliminating pre-trend biases across multiple outcomes.

(Figure A1) Cumulative effects of innovation on employment and LP growth



Notes: This figure shows the estimated cumulative effects of innovation on firms' employment and labor productivity growth, based on the DR estimators to estimate the ATT. The dark and light shaded areas represent 68% and 95% confidence intervals, respectively, constructed from the percentiles of 200 bootstrap replications.

(Figure A2) Cumulative effects of innovation on sale and markup growth



Notes: This figure shows the estimated cumulative effects of innovation on firms' sales and markup growth, based on the DR estimators to estimate the ATT. The dark and light shaded areas represent 68% and 95% confidence intervals, respectively, constructed from the percentiles of 200 bootstrap replications.

Appendix 2. Determinants of heterogeneous R&D research types

Section 4.2 in the main text discussed the determinants of innovation implementation. This appendix extends that analysis by examining the determinants of the firm's input effort—specifically, the expenditure allocated to different types of research: basic, applied, and development research. Understanding these inputs helps clarify the pre-innovation strategic choices of firms. Basic research refers to investigations aimed at advancing fundamental understanding, without direct practical application focus. Applied research involves efforts to verify the feasibility of practical applications or explore novel methods of utilization, while development research focuses on creating or improving new products, processes, or technologies.

Table A1 presents the estimation results from a generalized linear model (GLM) where the dependent variable is the log of expenditure per employee for each research purpose. The analysis reveals a systematic hierarchical pattern in R&D commitment: as research moves from the foundational (basic) to the application-focused (applied) and finally to the market-ready (development) stages, the expenditure becomes progressively more sensitive to the firm's labor productivity. This suggests that R&D expenditure is more strongly correlated with the firm's current productive efficiency when the research phase is closer to market realization. A notable contrast is observed in the coefficient for the age, which is positively significant for basic and applied research but negatively significant for development research. This suggests that organizational longevity (age) may reflect the structural stability and established research capability necessary to sustain long-horizon, complex foundational research efforts (basic and applied). Conversely, the negative association with development research implies that older firms may suffer from higher inertia or lower agility when committing resources to rapid, market-focused development activities.

Regarding financial factors and strategic focus, a high interest rate is positively and significantly associated only with basic and applied research; the coefficient for development research is statistically insignificant. This distinction suggests that the inherent high-risk nature of basic and applied research leads firms to pursue these endeavors even in financing environments associated with higher perceived costs, possibly reflecting a strategic commitment by well-positioned firms. Conversely, the leverage ratio exhibits a negative and significant correlation with all three types of research. This pattern suggests that firms with stronger balance sheets (low leverage) are structurally better equipped to finance and sustain long-horizon R&D efforts across the board, which are crucial precursors to eventual innovation implementation. These findings support the main text's narrative that while R&D intensity is a necessary input, financial health and strategic focus differentially drive the type of research, influencing the eventual implementation of product versus process innovation.

(Table A1) GLM estimation: determinants of research expenditure for each purpose

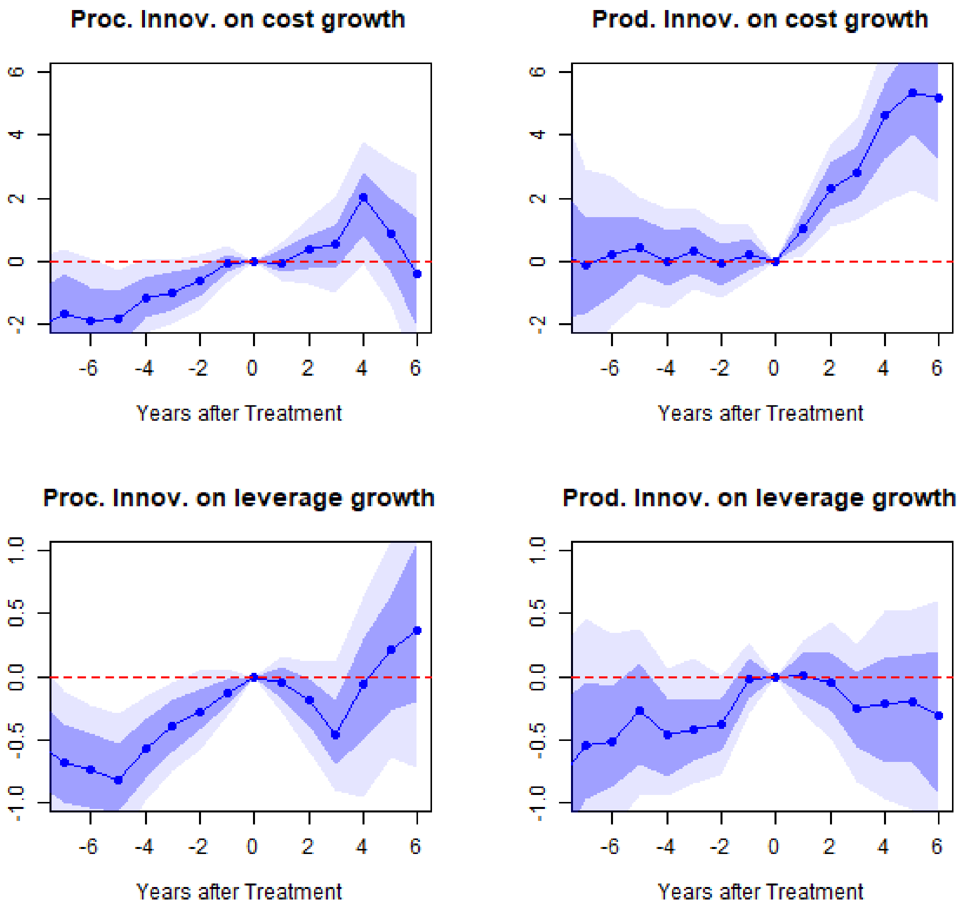
	log(Expenditure /Employee)		
	Basic	Applied	Develop
Industry Growth Rate (past 3 years)	-0.00026	-0.00127	0.00112
	(0.00080)	(0.00197)	(0.00106)
Employment Growth Rate (past 5 years)	-0.00225*	-0.00692***	-0.00547***
	(0.00125)	(0.00252)	(0.00178)
log(Age)	0.00168***	0.00324***	-0.00229***
	(0.00046)	(0.00072)	(0.00083)
log(Sales)*1,000	0.00175***	0.00362***	0.00129**
	(0.00000)	(0.00000)	(0.00000)
log(LP) *100	0.75595**	2.10914***	4.15357***
	(0.00327)	(0.00653)	(0.00535)
log(R&D Expenditure /Employee) *100	0.00382***	0.00780***	0.01030***
	(0.00001)	(0.00001)	(0.00001)
Interest Rate	0.08523***	0.08359***	-0.00491
	(0.02364)	(0.01293)	(0.02118)
Levarage Ratio	-0.00346**	-0.00302***	-0.00387***
	(0.00151)	(0.00117)	(0.00060)
Fixed Effects			
Industries	Y	Y	Y
Years	Y	Y	Y
Regions	Y	Y	Y
N	86,786	86,786	86,786
AIC	255,571	326,001	309,950

Notes: This table reports estimation results from a GLM model using three different sets of outcomes. The reported coefficients are marginal effects. Robust standard errors clustered at the industry and prefecture levels are shown in parentheses. *, **, and *** ndicate statistical significance at the 10%, 5%, 1% levels, respectively.

Appendix 3. Dynamic effects on financial and efficiency outcomes

This appendix extends the core dynamic results by investigating the effects of innovation on cost and financial outcomes, specifically cost growth and leverage ratio growth. As shown in Figure A3, process innovation yielded no statistically significant dynamic effects on either cost growth or leverage ratio growth across all post-treatment horizons. This finding further reinforces the main conclusion that process innovation does not translate into measurable efficiency gains or expansion for the average firm. Conversely, product innovation (upper-right panel) naturally leads to a significant increase in cost over the medium term. This is consistent with the firm expansion and simultaneous increases in sales and employment found in the main text (Figures 7 and 8). The effect on the leverage ratio (lower-right panel) remains non-significant, suggesting stable financial structuring during expansion.

(Figure A3) Cumulative effects of innovation on cost and levarage growth

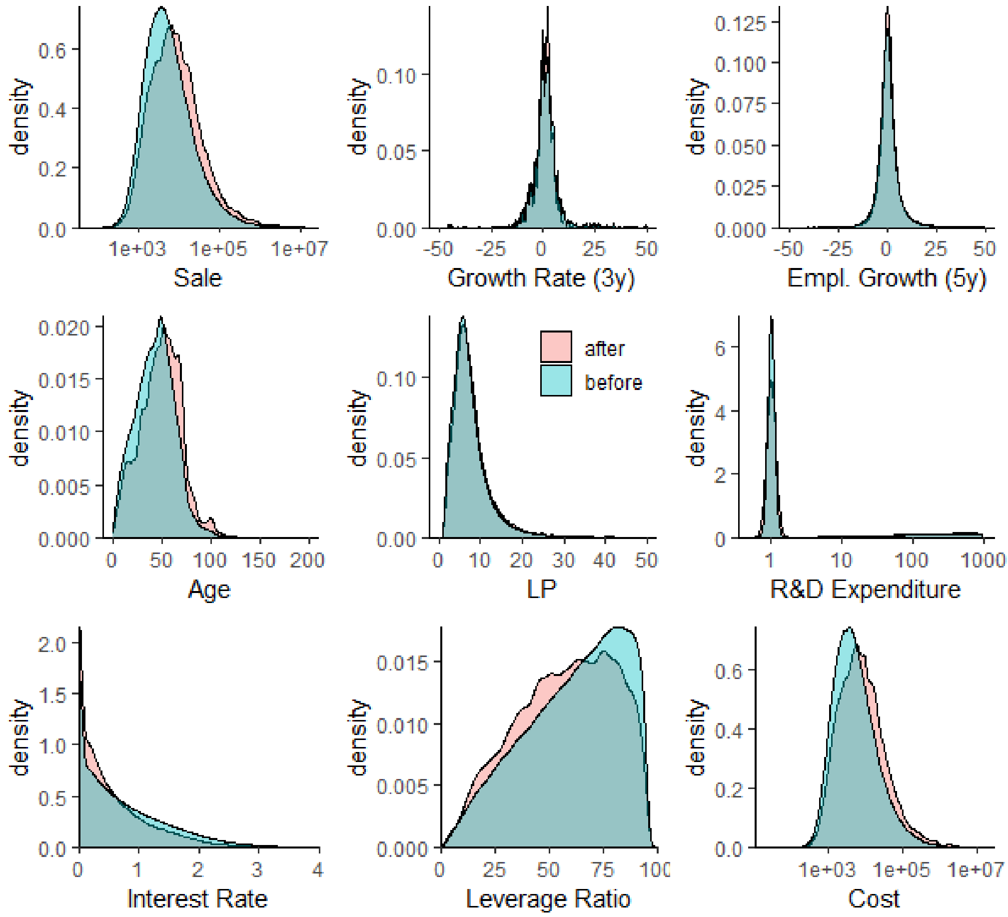


Notes: This figure shows the estimated cumulative effects of innovation on firms' cost and leverage growth, based on the DR estimators to estimate the ATT. The dark and light shaded areas represent 68% and 95% confidence intervals, respectively, constructed from the percentiles of 200 bootstrap replications.

Appendix 4. Comparison of sample distribution before and after matching

This appendix provides a visual comparison of sample characteristics to verify the absence of significant selection bias introduced by constructing our matched longitudinal panel from different survey frames. Figure A4 compares the density distributions of J-NIS responding firms ("before," blue) with the final constructed longitudinal panel dataset after successful matching with BSJBSA ("after," red) for key DR-DiD covariates. The density plots show the two distributions are highly similar across all key variables. This high degree of overlap confirms that minimal selection bias was introduced, providing crucial support for the representativeness of our final estimation sample

(Figure A4) Distribution of summary statistics before and after panel matching



Notes: This figure illustrates the density distributions of key pre-treatment covariates before and after sample matching. The blue region ("before" matching) represents the distribution of samples from the J-NIS responding firms. The red region ("after" matching) represents the distribution of samples in the final constructed longitudinal panel dataset. The x-axis indicates the value of the variable, and the y-axis indicates the density.