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Abstract

Workforce downsizing is an important management strategy that is assumed to allow firms to recover from business downturns. Using administrative data on the population of manufacturing plants and their products in Japan, we examined how plants that engage in layoffs reallocated their internal resources and whether they eventually increased their productivity or secured innovative gains. Accounting for staggered timings of layoff events, we found that such plants successfully reduced their production levels by reducing both capital and labor inputs. However, even years after the layoff announcement, those plants failed to outperform control plants in terms of introducing new products or increasing productivity. These results were accompanied by a disproportionate decline in the proportion of young workers and lower compensation among senior workers.

Keywords: layoff, employee downsizing, product innovation, productivity, firm-specific skill investment, Great Recession, staggered difference-in-differences

JEL Classification: E32; J11; J15; J24; J26

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1　Introduction

Workforce downsizing is an important management decision for firms to recover from business downturns. By laying off workers, firms intend to allocate their internal resources efficiently in response to external changes to prepare themselves for the next stage of growth.[1]

However, whether downsizing leads firms to a successful recovery and eventually promotes innovation remains controversial. Previous studies have reported non-positive effects of firm downsizing. For instance, in the context of Spanish firms, Muoz-Bulln and Snchez-Bueno (2011) found no evidence to support an improvement firms' financial performance, such as in their ROA, after a reduction in their workforce. Similarly, Kawai (2014) established a negative correlation between downsizing and the subsequent sales growth among Japanese multinational firms. In their extensive review of downsizing literature conducted until 2008, Datta et al. (2010) reported that studies on stock market returns predominantly found negative returns after a firm's layoff announcement. Previous studies typically assessed the impact of downsizing on firms' aggregate performance. However, there exists limited information regarding how downsizing firms allocate their internal resources and whether they can increase their productivity or secure innovative gains.

This study used the administrative data of manufacturing plants in Japan to provide the first comprehensive evidence of downsizing effect on firms' production decisions, productivity, and product innovation along with supplementary evidence on employees' age distribution at each plant. We first extracted layoff announcement information for firms listed on Japanese stock exchanges. We then compared the performance trajectories of plants whose headquarters announced layoffs to those of their similar counterparts without any layoff announcements. Plants with layoff announcements may be systematically different from other plants in terms of managerial traits or production technologies, raising concerns regarding causal interpretations. To address this issue, we carefully con-

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[1]In fact, this is an important reason why policy makers are concerned about making employment protection legislation too stringent. Comparing establishments with or without a high firing cost, previous studies reported that strict firing restrictions significantly reduced firm productivity in China (Guo et al., 2021), India (Schwab, 2020), Italy (Cingano et al., 2016), Japan (Okudaira et al., 2013), Sweden (Bjuggren, 2018), and the US.(Autor et al., 2007).

structed appropriate comparison groups by following recent advancements in the staggered difference-in-difference (DID) literature (Baker et al., 2021; Borusyak et al., 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and DHaultfuille, 2020; Goodman-Bacon, 2021; Imai and Kim, 2021; Sun and Abraham, 2021; Athey and Imbens, 2022). We also merged information on employee age distribution from another administrative survey to interpret the mechanism in light of firm-specific human capital investments.

Based on large-scale layoffs announced between 2008 and 2012, we found that layoff plants had significantly lower employment levels than control plants after the announcement. According to our estimates, layoff plants reduced their employment level by approximately 10%, and they could not recover at least in the succeeding four years. Their production level also fell by 20%, followed by an even stronger reduction in capital inputs by 30%. These results suggest that the plants successfully adjusted their scale of production by announcing layoffs. However, our analyses also revealed that layoff plants did not outperform control plants in terms of labor productivity, even years after the layoff event. One reason for this non-positive effect is the substantial reduction in capital intensity. Despite a large reduction in the labor force, their capital intensity per worker was reduced owing to a stronger cutback in their capital. In fact, we found that plants did not introduce new products or abolish existing ones in comparison to the control plants, implying a sluggish level of investment. Thus, employee downsizing helped plants scale down their production level; however, it did not initiate subsequent product innovations or productivity gains, at least during our sample period.

We further explored the implications of firm-specific skill investments in interpreting the mechanisms behind the absence of innovation and productivity gains. An important concern for layoff firms is the loss of skilled workers. In particular, when both firms and workers invest in workers' firm-specific skills, the decision regarding who should be laid off is a sensitive divestment decision for firms. Lazear and Gibbs (2014); Lazear and Freeman (1997) rationalizes this decision in light of human capital investment theory. According to their argument, employers would benefit by laying off the youngest and oldest work-

ers first because firms either invest less or recoup more rents from these workers (Lazear and Gibbs, 2014; Lazear and Freeman, 1997). Based on a subset of plants with merged age information, we estimated the impact of layoff announcements on employees' age distribution within each plant. Consistent with the theoretical argument, we found that employers' age distribution was significantly skewed toward middle-aged workers after the layoff announcement. This is reasonable because firms retain a relatively larger share of workers with the highest outstanding rents in terms of firm-specific skill investment. However, our analyses revealed that such a change also incurred costs: an increase in the proportion of middle-aged workers was compensated by a significant decline in the proportion of employees in their 20s rather than those in their 50s or 60s. Moreover, our supplementary analyses show that workers in their 50s had to work for the same number of hours, but with significantly lesser bonuses, after the layoff announcement. Taken together, the results of this study highlight the important detriments of layoffs as a means of internal resource allocation: a disproportionate decline in the proportion of young employees and deteriorating working condition among the remaining senior employees.

Our study contributes to the downsizing literature in three ways. First, it provides the first direct evidence of product innovation by relying on large-scale administrative data. Although this study does not provide an inclusive assessment of organizational innovation, it goes beyond earlier studies by analyzing the actual innovative outcomes at the product level along with the internal resource allocations within the plant. Second, we contribute to the downsizing literature by carefully accounting for the staggered timings of layoff events. Some recent studies have raised serious concerns in applying the event study approach when the treatment has multiple timings and heterogeneous effects over time (Baker et al., 2021; Borusyak et al., 2021; Callaway and Sant'Anna, 2021; de Chaise-martin and DHaultfuille, 2020; Goodman-Bacon, 2021; Imai and Kim, 2021; Sun and Abraham, 2021; Athey and Imbens, 2022). Intuitively, the bias arises owing to the inclusion of early-treated groups in the control group in estimating the treatment effect for later-treated groups. After accounting for this bias, some prominent findings in finance and accounting

publications failed to survive (Baker et al., 2021). As layoffs occur at different points in time for each firm, it is essential to follow the proposed methods in the context of our study. To the best of our knowledge, our study is one of the first to apply a staggered DID framework in downsizing literature to provide a valid causal inference.

Finally, we quantified one possible mechanism by which previous studies often found non-positive effects of employee downsizing on firm performance, namely, a breach of long-run commitment to employers, particularly among young employees. According to the theory of firm-specific skill investment, employees are better off by leaving the current firm and investing in new relation-specific skills at a different firm once they view the layoff announcement as a signal of lower future returns. As young employees have a longer period to recoup their return on investment and, thus, have a higher option value to switch their employers, they are more likely to leave the firm. Consistent with this idea, we found a significant disproportionate decline in the share of young workers. Although relation-specific skill investment is relevant to any organizations seeking long-term commitment with their employees, no empirical studies have tested its implications for the downsizing strategy. We take advantage of a Japanese setting in which the majority of firms still engage in relation-specific investments with their employees. An important takeaway to management is that for firms pursuing long-term relationships with their employees, opting for a large-scale layoff is a tricky option, as it triggers voluntary quits disproportionately among young employees. Management in such a firm may better plan reskilling or upskilling slack labor beforehand as an alternative reallocation option before the emergence of a business crisis.

The rest of this paper is organized as follows. Section 2 introduces the datasets used in the analyses. Section 3 describes the identification strategies used in this study. Section 4 presents the results and robustness tests. Section 5 concludes the study.

2 Data

2.1 Main Data

Our main analysis draws on plant-level panel data from the Census of Manufacture, which is conducted annually by the Japanese Ministry of Economy, Trade, and Industry. The Census of Manufacture covers nearly the entire population of plants in the manufacturing sector in Japan. It contains detailed information on factor inputs and outputs produced at each plant. Using this information, we calculated the plants' value-added, capital intensity, Total Factor Productivity (TFP), and labor productivity.[2] We start our analysis with the annual files from 2005 to 2016 that cover all plants with 30 or more employees (*Kou Hyou* panel).[3]

One advantage of using the Census of Manufacture is that we can proxy the extent of product innovation by relying on the 6-digit level records of products manufactured at each plant. The 6-digit level of product information is sufficiently detailed to reflect major product innovation.[4] We aggregated the product information for each plant at each time period by counting the number of products they produced. More specifically, a new product is defined as a product produced in the survey year but not in the previous year. Similarly, an abolished product is the product produced in the survey year but not in the next year. The net increase in the number of products was calculated as the number of new products minus the number of abolished products. We then merged this information with layoff announcement records to examine the impact of large-scale layoffs on firms' product dynamics. Table 1 presents the summary statistics of the main data. On average, plants in our sample produced 2.3 products, abolished 0.14 products, and added 0.15 products per

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[2]To calculate TFP, the average of the labor shares by each industry s (α_s) was taken. We then calculated the TFP of plant i at time t as $lnTFP_{it} = lnVA_{it} - \alpha_s lnL_{it} - (1 - \alpha_s)lnK_{it}$, where VA, L, and K denote value-added, number of regular workers, and fixed assets, respectively.

[3]The survey also has other types of annual files that contain information on all plants with 29 or fewer employees (*Otsu Hyou* panel). As these files lack information on fixed assets, we decided not to use them in this study.

[4]For example, batteries are broken down to "lead battery (309111)," "alkaline battery (309112)," and "lithium-ion battery (309113)," among others. Dekle et al. (2021) used the same 6-digit product data to examine product dynamics over business cycles.

year.

To explore the impact of layoff announcements on firm-specific investment, we complemented our analysis with age composition information available in the Basic Survey on Wage Structure (BSWS) conducted by the Ministry of Labour, Health, and Welfare. As Japan is still known for its lifetime employment practice (Kambayashi and Kato, 2016), age is an important proxy for the extent of firm-specific skill investment. By drawing on the employee questionnaires of the BSWS, we calculated age distributions along with means of bonus and work hours within each plant and merged the information with plant-level observations in Census of Manufacture.[5] The bottom half of Table 1 shows the summary statistics for the proportion of employees in a specific age group, along with other outcome variables. As the BSWS randomly samples a subset of employees in the surveyed plants, distributional information (e.g., means and proportions) is subject to measurement error.[6]

2.2 Layoff Announcement

Our data on layoff announcements were taken from a survey compiled by Tokyo Shoko Research Ltd. (TSR).[7] The survey collects information on large-scale layoffs announced by major listed companies and OTC-registered companies.[8] It contains the layoff announcements of well-known global corporations. We merged the firm-level layoff announcements provided by the TSR with plant-level observations of the Census of Manufacture by the telephone number of the plant's headquarters. Figure 1 shows the number of plants whose headquarters announced layoffs in the merged dataset. Unsurprisingly, the number of lay-

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[5]Plant-level observations in the BSWS and Census of Manufacture were merged by key identifiers available in Economic Census for Business Activity (METI and MIAC), Economic Census for Business Frame and Establishment and Enterprise Census of Japan (MIAC).

[6]The employee sampling rate is determined by the number of regular workers and industrial classification. It is set between 1 (total number) and 1/5 when the number of regular workers is 499 or less and between 1/10 and 1/90 when the number of regular workers is 500 or more. The larger the establishment size, the lower is the employee sampling rate.

[7]TSR is a major credit research company in Japan, mainly engaged in the credit research of domestic and overseas companies as well as the construction of database based on corporate information. We thank TSR for providing us with layoff announcement data.

[8]The survey is based on "the Disclosure of Corporate Information" section of the Timely Disclosure of Corporate Information.

offs surged during the Great Recession of 2009.

To exploit all announcement events in our estimations, we used the unbalanced panel data of plants. Thus, our estimate measures the aggregate treatment effect, including the effects of compositional changes arising from a plant's entry or exit. To understand how the compositional effect affects the aggregate treatment effect, we also examined the impact of layoff announcements on the probability of long-term selective attrition (see Section 4.2 and Appendix Table 1).

It is important to note that the layoffs in our dataset were announced as buyout offers to employees. Some firms strategically target buyout offers to specific age groups by setting a minimum age requirement. Although some of our layoff announcement data contain age requirement information, we did not use this information in our estimations owing to a small sample size or the lack of statistical power. Instead, we examined whether layoff announcements induced any changes in the age distributions of employees at the targeted plants by relying on the BSWS data. We used the results of this analysis to interpret the mechanism behind our main results.

3   Identification Strategy

To evaluate the consequences of layoff announcements on firm performance, we adopted an event study approach. In this approach, we compared the performance trajectories of plants with layoff announcements to those of their similar counterparts without any layoff announcements. We start our specification with a standard DID model with two-way fixed effects.

$$Y_{it} = \sum_{s=-w}^{w} \gamma^s I(event_{it}^s) + x_{it}\beta + \delta_t + \theta_i + \epsilon_{it}, \tag{1}$$

where w is an arbitrary event window. Y_{it} is an outcome variable for plant i in year t, such as the number of new products, productivity, or proportion of young workers in manage-

rial positions. The treatment indicator $I(event_{it}^s)$ takes a value of one if plant i announces layoffs at s years from period t. The model also controls for a vector of plant characteristics, x_{it}. To identify this model, treated plants should have followed the same outcome path as the control plants, had the treated plants not been affected by the layoff announcement. Researchers typically test the validity of this common trend assumption by examining the magnitude of the estimates of γ^s for $s \leq -1$ and ensuring that the treated and control plants follow the same outcome trends prior to the treatment event. Such a DID specification has been adopted across a wide range of studies, including prominent works in finance and accounting (Beck et al., 2010; Fauver et al., 2017; Wang et al., 2021).

However, recent advancements in the econometrics literature have raised serious concerns about estimating DID models when the timings of treatments are staggered (Baker et al., 2021; Borusyak et al., 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and DHaultfuille, 2020; Goodman-Bacon, 2021; Imai and Kim, 2021; Sun and Abraham, 2021; Athey and Imbens, 2022). Particularly, the standard DID model, such as equation (1), treats early adopters as control units when estimating the treatment effect of late adopters. When the treatment has multiple timings and heterogeneous effects across time, the dynamic evolution of the treatment effect has a bias on the DID estimate owing to the inclusion of early adopters in the comparison group. In fact, the DID estimate can provide the opposite sign of the true average treatment effect on the treated. In his replications of the earlier studies with a standard DID approach in finance and accounting journals, Baker et al. (2021) showed that some important findings in these studies failed to survive after correcting for the bias arising from the inclusion of early adopters in the control group.[9] To identify the treatment effect of staggered events, we need to construct appropriate control groups for each of the treatment events and ensure the validity of the common trend assumption for

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[9]By applying a standard DID specification to bank branching deregulations that occurred at different points in time across the US, Beck et al. (2010) found that the deregulation reduced state-level income inequality; however, this result no longer holds in specifications correcting for the inclusion of early adopters in a comparison group (Baker et al., 2021). Baker et al. (2021) also presented similar replication failures for Fauver et al. (2017), which showed the positive impact of corporate board reforms on firm values, and for Wang et al. (2021) which found a negative impact of the staggered legalization of stock repurchases on firm investments.

each of these events.

To overcome the issues arising from staggered DID, this study adopted a strategy suggested in recent literature — stacked event-by-event approach proposed in Cengiz et al. (2019). In particular, we first define "event" by the timing of firms' announcement of layoffs. We then created an event-specific dataset by stacking the treated and "clean" control plants. For the 2009 event, for example, we stacked all the plants that announced layoffs in 2009 and control plants that never experienced layoffs during our sample period into one dataset.[10] By stacking event-specific data in this manner, we avoided early adopters in the control group. For each event-specific stacked dataset, h, we estimated the following equation:

$$Y_{ith} = \sum_{s=-w}^{w} \gamma^{sh} I(event_{ith}^s) + t \cdot \tau_{ph} + t \cdot \tau_{jh} + \delta_{th} + \theta_{ih} + \epsilon_{ith}, \tag{2}$$

where Y_{ith} is an outcome variable for plant i in year t for dataset h. Similar to equation (1), we purged out the plant fixed effects specific to dataset h. We also controlled for the event-specific region (p) and 3-digit industry (j)-specific linear trends, $t \cdot \tau_{ph}$, and $t \cdot \tau_{jh}$ to separate unobserved shocks specific to region or industry. The estimated treatment effects, $\hat{\gamma}^{sh}$, compared the performance trajectories between the treated and control plants for $s > 0$. We tested the validity of the common trend assumption in dataset h by examining the magnitude of the estimates of γ^{sh} for $s \leq -1$.

To estimate a single set of average treatment effects γ^s across all event years and provide a comprehensive assessment, we stacked all the event-specific datasets:

$$Y_{ith} = \sum_{s=-w}^{w} \gamma^{s} I(event_{ith}^s) + t \cdot \tau_{ph} + t \cdot \tau_{jh} + \delta_{th} + \theta_{ih} + \epsilon_{ith}. \tag{3}$$

Inclusion of the term δ_{th} essentially allows us to separate the dynamic treatment effects from year effects specific to the event group.

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[10]Control plants in our sample includes those plants which received employment adjustment subsidy. Thus, the estimated treatment effects reflect the difference between layoff plants and plants receiving the subsidy.

4 Results

4.1 Are Layoff Announcements Exogenous?

Firms announcing layoffs may be systematically different from other firms a priori in terms of unobserved managerial traits or technology to substitute labor with capital. As such differences can mask the true causal effect of layoff announcements, it is important to compare layoff plants with those of otherwise identical plants. To ensure the common trend assumption, we estimated equation (2) separately for each year and examined whether there were any systematic differences in the outcomes between layoff plants and their control plants prior to the layoff announcement. We took the logarithm of the number of employees as the dependent variable. As our main data cover the years between 2005 and 2016, we fixed our event window at three years before and after layoff announcements ($w = 3$) to enhance comparisons across event years.

Figure 2 presents the estimates of γ^{sh} for each event year. Most of the event years show significant drops in the number of employees following the announcement. This is consistent with the original purpose of layoff announcements. Except for 2010, plants experienced approximately 15 to 30 % reduction in their workforce at some point in the following years. Plants showed immediate declines in 2009, 2011, and 2012. However, this was not evident for the remaining event years, although most of their estimates still showed a negative impact. One possible reason is that firm-level layoff information does not necessarily identify the plants or branches targeted for layoffs.[11] Moreover, the estimates for the 2008 and 2010 events had relatively large confidence intervals, implying a lack of statistical power due to the smaller number of treated plants (see Figure 1).

Importantly, the estimates for the pre-announcement periods are insignificant and close to zero, except for the layoff announcements in 2013. Thus, except for the 2013 event,

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[11]We matched the layoff information by the telephone numbers of the headquarters; however, the phone numbers of some headquarters are not available in the Census of Manufacture. It is also possible that branches targeted at the firms' layoff announcements were not registered as manufacturing establishments; the firms did not target the manufacturing branches for the layoff.

the treatment and control plants were comparable in that they followed the same outcome trends before the event year. We consider this to be an evidence of the exogeneity of the layoff shock between 2008 and 2012, conditional on industry- or region-specific linear trends: firms announced layoffs presumably because of unexpected or idiosyncratic demand shocks during this period. On the contrary, the 2013 layoff announcements predict the pre-treatment employment level of treated plants. It is likely that the 2013 layoff announcements were targeted at those plants that had redundant workers even three years prior to the announcement. In the following analyses estimating equation (3), we stacked event-by-event datasets between 2008 and 2012 but excluded the 2013 dataset to ensure the validity of the common trend assumption.

4.2   Impact of Layoff Announcement on Firm Performance and Product Innovation

This section examines the performance dynamics that plants followed after announcing large-scale layoffs. We stacked event-by-event datasets between 2008 and 2012 and estimated equation (3) using several performance measurements as dependent variables. Figure 3 shows the estimation results. Consistent with Figure 2, plants reduced their employment levels by approximately 10% after the firms' layoff announcement. This effect persists for at least four years following the announcement. Firms also significantly reduced their value-added, $ln(ValueAdded)$, and fixed assets, $ln(K)$. A gradual reduction in capital occurred, implying high adjustment costs for fixed assets. Changes in input factors suggest that firms' primary reason for the layoff was to reduce the scale of their production, which was most likely driven by a negative demand shock.

While plants successfully adjusted the production level by layoffs, the adjustment did not lead to a substantial improvement in their productivity levels. Figure 3 also shows that the plants' total factor productivity, $ln(TFP)$, plummeted and took four years to recover to a level comparable to that of the control plants. As expected, capital intensity,

$ln(K/L)$, increased in the year of the layoff announcement; however, it continued to decline, consistent with a substantial reduction in fixed assets, $ln(K)$. Thus, plants decreased their level of capital more than they did their employment level. Even after the layoff announcements, the plants had redundant labor. In fact, the layoff plants had lower labor productivity, $ln(ValueAdded/L)$, compared to the control plants, although the differences were not significantly different from zero. To summarize, we obtained no evidence that the layoff plants improved their performance in comparison to their control counterparts, although they adjusted their scale of production.[12]

Figure 4 shows that layoff announcements did not help plants promote product innovations in subsequent years. Here, equation (3) was estimated by replacing the dependent variables with the product information available in the Census of Manufacture. The layoff plants did not add new products or abolish the existing products when compared against their comparison group. The changes in the total number of products were also unaffected. Thus, the layoff plants did not recover in the sense that they did not engage in any product innovation, even years after the layoff announcements.

Appendix Figures and Table present the results of the sensitivity analyses in light of longer-term impacts as well as selective attrition. In summary, none of these analyses alters our main implications in Figures 3 and 4. The long-run impact of extending the estimation window are depicted in Appendix Figures 1 and 2. Here, we focus on a stacked dataset specific to the 2009 event and estimate equation (2) over an extended sample period from 2005 to 2016. Thus, we estimated the treatment effect for up to seven years after the layoff announcement. Our results in this extended window are similar to the previous findings presented in Figures 2 and 3. However, we observed slightly different impacts on productivity. Appendix Figure 1 shows no significant negative impacts of layoff announcements on total factor productivity and labor productivity. We also observe a recovery in capital intensity six years after the announcement. The increase in capital intensity was driven by

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[12]It is important to note that our estimations are based on plant-level dataset, rather than firm-level. Our sample includes both plants affected by the headquarter's layoff announcement and the plants of the same firm but unaffected by layoff. In this sense, our treatment estimates measure the intention to treat (ITT) effect.

an increase in fixed assets. However, the value-added was still significantly lower among the layoff plants, even seven years after the event. We also found no clear evidence of significant improvements in plants' product creations in Appendix Figure 2, although the estimates were admittedly imprecise. Again, the layoff helped to scale down their production level; however, it did not trigger any substantial product innovations, even in the longer span.

Appendix Table 1 demonstrates whether the selective attrition of plants explains our main findings. Since we estimated our models on unbalanced panel data of plants, the results obtained measure the aggregate treatment effects, including the effect arising from compositional changes owing to plants' entry or exit. If layoff announcements affected plants' decision to exit the market, in particular, the negative estimates of plants' performance would be underestimated owing to survivorship bias. This point was examined by first considering each event dataset h and constructing cross-sectional data containing a plant's attrition dummy for the plants observed in the event year, as demonstrated in Appendix Table 1. We then estimated the logistic model of a plant's attrition probability separately for each event year (h):

$$Prob(Attrition_{ih} = 1) = x_i\beta^h + \gamma^h I(event_{ih}) + \epsilon_{ih}, \qquad (4)$$

where the dependent variable is an attrition indicator that takes one if the plant i is never observed after three years from the event year. We included industry and region dummies as plant control variables x_i. Appendix Table 1 shows the odds ratios for the impact of layoff announcements for each event year.

4.3 Mechanism: Firm-specific Skill Investment

One important concern for layoff firms is the possibility of losing highly skilled workers. In particular, when both firms and workers commit to a long-term relationship, such as in Japan, firms are concerned about dismissing the accumulated firm-specific human capital.

This section tests whether the layoff announcement skewed workers' distribution to a specific age group and examines whether the loss in firm-specific human capital explains why plants did not excel in terms of product innovations even years after adjusting their scale of production.

To serve this purpose, we estimated equation (3) by replacing the dependent variables with the proportion of employees in a specific age group at each plant. We constructed the proportions from the employee questionnaires of the BSWS. We estimated the model for plants that appeared in both the Census of Manufacture and BSWS. Due to the availability of key identifiers to merge the BSWS and the Census of Manufacture, we used stacked event-by-event datasets only for the event years between 2008 and 2010. Therefore, a sample in this estimation is a subset of the main sample used to estimate Figures 3 and 4 and should be considered as providing complementary evidence.

Figure 5 presents the estimation results for each age group. The bottom-right graph shows the impact on the mean years of employees' tenure at each plant. We found that layoff announcements affected employees' distribution unevenly across age groups. In particular, layoff announcements did not significantly reduce the proportion of employees in their 50s or 60s. Since layoff announcements reduced the number of employees by 10%, according to Figure 4, the number of employees decreased even if the proportion remained the same. We originally expected that the layoff announcement would shift the age distribution downward because some firms targeted buyout offers to older employees. However, we found that the layoff announcement skewed the age distribution toward the middle age: the layoff announcements increased the proportion of employees in their 40s one year after the announcement, while they decreased the proportion of employees in their 20s.

Lazear and Freeman (1997) rationalized employer's strategy regarding who should be laid off when they have invested in the employees' firm-specific skill.[13] One important implication is that employers are better off by targeting the layoff to the employees at both

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[13]Lazear and Gibbs (2014, 82-85) provided a clear illustration of this idea.

ends of the age distribution: firms have not invested so much in those who just started their career; firms have already recouped their returns from the earlier investment in firm-specific skills from the workers close to their retirement. Thus, employers should not target workers in the middle of their career for their layoffs since these workers have the highest outstanding rents to recoup over the coming years. In light of this theoretical implication, it is reasonable that the plants in our sample retained a relatively large share of workers in their 40s than control plants a year after the announcement because this cohort is presumably the one with the highest outstanding rents in terms of firm-specific skill investment.

However, our analyses also revealed that such a change comes at some cost. First, layoff plants had a disproportionately lower share of young employees than control plants. According to Figure 5, the increase in the proportion of middle-aged workers was compensated by a significant decline in the proportion of employees in their 20s compared to those in their 50s or 60s. Studies argue that creativity declines with age (Acemoglu et al., 2014; Florida, 2002), which may explain the stagnant productivity and innovation. Our supplementary analysis in Appendix Figure 3 implies that the reduction in the proportion of employees in their 20s occurred owing to increased separation among this cohort.[14] According to firm-specific skill investment theory, employees decide to invest in skills specific to their firms when they foresee sufficient long-term returns. If the layoff announcement signals a lower return on their firm-specific skill investment in the future, employees may be better off by leaving the firm and investing in new relation-specific skills at a different firm. As younger employees have a longer period to recoup the return to the investment and thus have a higher option value to switch their employers, they are more likely to leave the firm. Therefore, Figure 5 highlights an important detriment of layoffs as a means of a firm's internal resource allocation: it triggers a breach of long-run commitment to employers, particularly among young employees, once they foresee it as a signal of lower return

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[14]Unfortunately, our datasets do not contain the information on voluntary quits or acceptance of buyout offers for the layoff. Instead, we estimated the same model as before but with a different dependent variable: the number of new graduates hired, available in the BSWS. The estimation results in Appendix Figure 3 show that layoff announcements have no significant impact on the number of newly hired graduates. As Japanese firms hire young full-time employees mainly through new graduates, we conjecture that the reduction in the proportion of those in their 20s occurred owing to increased separations among the same cohort.

to their vested investment.

Another explanation for the absence of productivity or innovative gains is the deteriorated working condition of employees in their 50s. These employers usually retrieve returns on their earlier investment in firm-specific human capital in the form of high wages. To explore the impact of layoff announcements on older employees, we estimated the impacts on plant-level mean bonus or the number of hours employees worked by age group, which we constructed again from the employee questionnaires of the BSWS. The estimation results in Appendix Figures 4 and 5 show a significant reduction in the annual bonus for employees in their 50s after the layoff announcement; however, their work hours were unaffected.[15] Thus, senior employees who remained in the firm worked for the same hours but received lesser compensation. These results are consistent with studies reporting the demotivation effect of firm downsizing on the remaining workforce (Kawai, 2014).

The evidence presented in this section should be interpreted with a caveat, since it is based on plant observations in the BSWS and does not constitute the full sample that we used in the main analysis in the previous section. Moreover, the BSWS was not originally designed as a longitudinal survey. Plants with low sampling rates are likely to be replaced in the next survey year.[16] Thus, the estimated impact of layoff announcements on the BSWS sample is subject to compositional changes across survey years. More specifically, significant changes in the proportion of employees in their 20s and 40s were observed only in the first year, following a layoff announcement. Owing to the limitations of the BSWS, we were unable to identify whether these temporal changes were truly transitory or driven by the replacement of plants in the BSWS sample.

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[15]This result is in contrast to Genda et al. (2015), who reported that the working hours of regular male employees increased at downsizing firms based on the data in the early 2000s. As the BSWS is an administrative survey of employers, our information on work hours may be understated by employers. We admit that the estimates shown in Appendix Figure 5 are subject to measurement errors and are overestimated if layoff plants tend to understate working hours. The true impact on work hours may be negative. However, we consider that this possibility does not change our implications.

[16]Some plants with high sampling rates remain in the sample. The larger the establishment size, the higher the sampling rate.

5 Discussion and Conclusion

Firms can recover from business downturns in several ways. We explored the mechanism of workforce downsizing by examining how layoff firms reallocated their internal resources and whether they were able to eventually increase their productivity or secure innovative gains. To serve this purpose, we exploited administrative data on an entire population of manufacturing plants in Japan along with 6-digit product replacement records at each plant. We also complemented our analysis with another administrative survey to estimate the impact on the age distribution of employees at each plant.

Relying on the large-scale layoffs announced between 2008 and 2012 in Japanese listed firms, we found that employee downsizing helped plants reallocate their internal resources and scale down their production level; however, it did not initiate subsequent productivity gains or product innovations even years after the layoff event. More specifically, we found that layoff plants reduced their employment level by approximately 10%. Their production levels also fell by 20%, followed by an even stronger reduction in capital inputs by 30%. Despite a large reduction in the labor force, the capital intensity per worker was *reduced* owing to an even stronger cutback in their capital. In fact, we found that layoff plants did not introduce new products or abolish the existing ones in comparison to the control plants, implying a sluggish level of investment. We also found that employees' age distribution was significantly skewed toward middle-aged workers after the layoff announcement. Thus, firms adopted an efficient strategy in that they retained workers with the highest outstanding rents in terms of firm-specific human capital investment (Lazear and Gibbs, 2014; Lazear and Freeman, 1997). However, our analyses revealed that such a change also incurred costs: an increase in the proportion of middle-aged workers was compensated by a significant decline in the proportion of employees in their 20s rather than those in their 50s or 60s. Moreover, our supplementary analyses show that workers in their 50s had to work for the same number of hours, but with significantly lesser bonuses, after the layoff announcement. Taken together, the results of this study highlight the im-

portant detriments of layoffs as a means of internal resource allocation. The loss of young employees and deteriorating working condition among the remaining senior employees may explain why layoff plants did not increase productivity or secure innovation. An important takeaway to management is that for firms pursuing long-term relationships with their employees, opting for a large-scale layoff is a tricky option, as it triggers voluntary quits disproportionately among young employees. Management in such a firm may better plan reskilling or upskilling slack labor beforehand as an alternative reallocation option before the emergence of a business crisis.

Table 1: Summary Statistics

|	N	Mean	SD	P25	P50	P75
$ln(L)$	477023	4.37	.81	3.76	4.16	4.78
$ln(K)$	477023	10.12	1.68	9.16	10.09	11.09
$ln(ValueAdded)$	477023	11.12	1.27	10.28	10.93	11.79
$ln(TFP)$	477023	3.88	0.9	3.39	3.89	4.39
$ln(K/L)$	477023	5.75	1.34	5.1	5.87	6.56
$ln(ValueAdded/L)$	477023	6.75	.83	6.28	6.72	7.19
N of new products	477023	0.15	0.51	0	0	0
N of abolished products	477023	0.14	0.5	0	0	0
N of total products	477023	2.3	1.79	1	2	3
Proportion of employees						
20s	36727	0.18	0.11	0.1	0.17	0.25
30s	36727	0.26	0.11	0.18	0.25	0.33
40s	36727	0.25	0.11	0.17	0.24	0.32
50s	36727	0.23	0.12	0.14	0.21	0.3
60s	36727	0.06	0.08	0	0.04	0.09
Mean tenure	36727	12.98	5.09	9.24	12.63	16.44
N of hired new graduates	36727	5.29	16.73	0	1	4
Mean annual bonus (in 10^4JPY $\approx$ 90USD)	36727	71.94	54.84	28.95	62.55	105.44
Mean monthly hours of work	36727	175.26	21.8	162.4	175.3	188.67

Source: Plant-level observations in Census of Manufactures, from 2005 to 2016. Age information is available only for those plants also observed in Basic Surveys on Wage Structure.
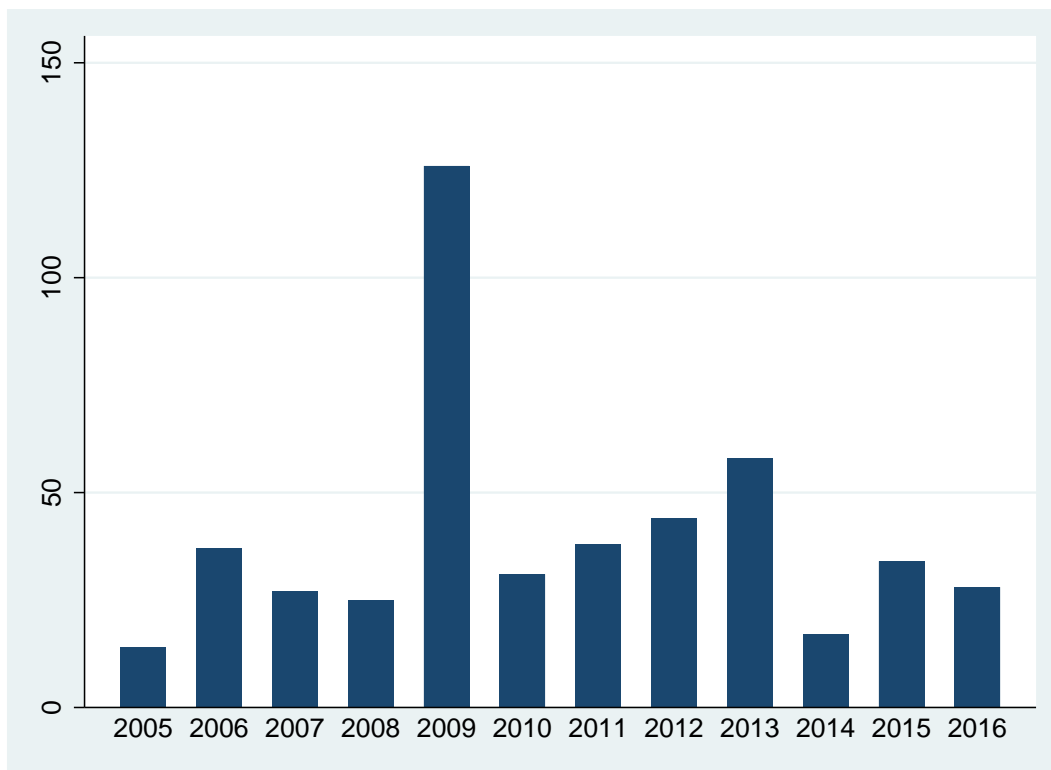
**Figure 1: Number of Plants Affected by Layoff Announcement**

Note: Bars indicate the numbers of plants whose headquarters announced buyout offers to lay-off their employees in our main sample of Census of Manufacture (METI), 2005-2016. Layoff an-nouncement information is taken from a survey conducted by TSR.
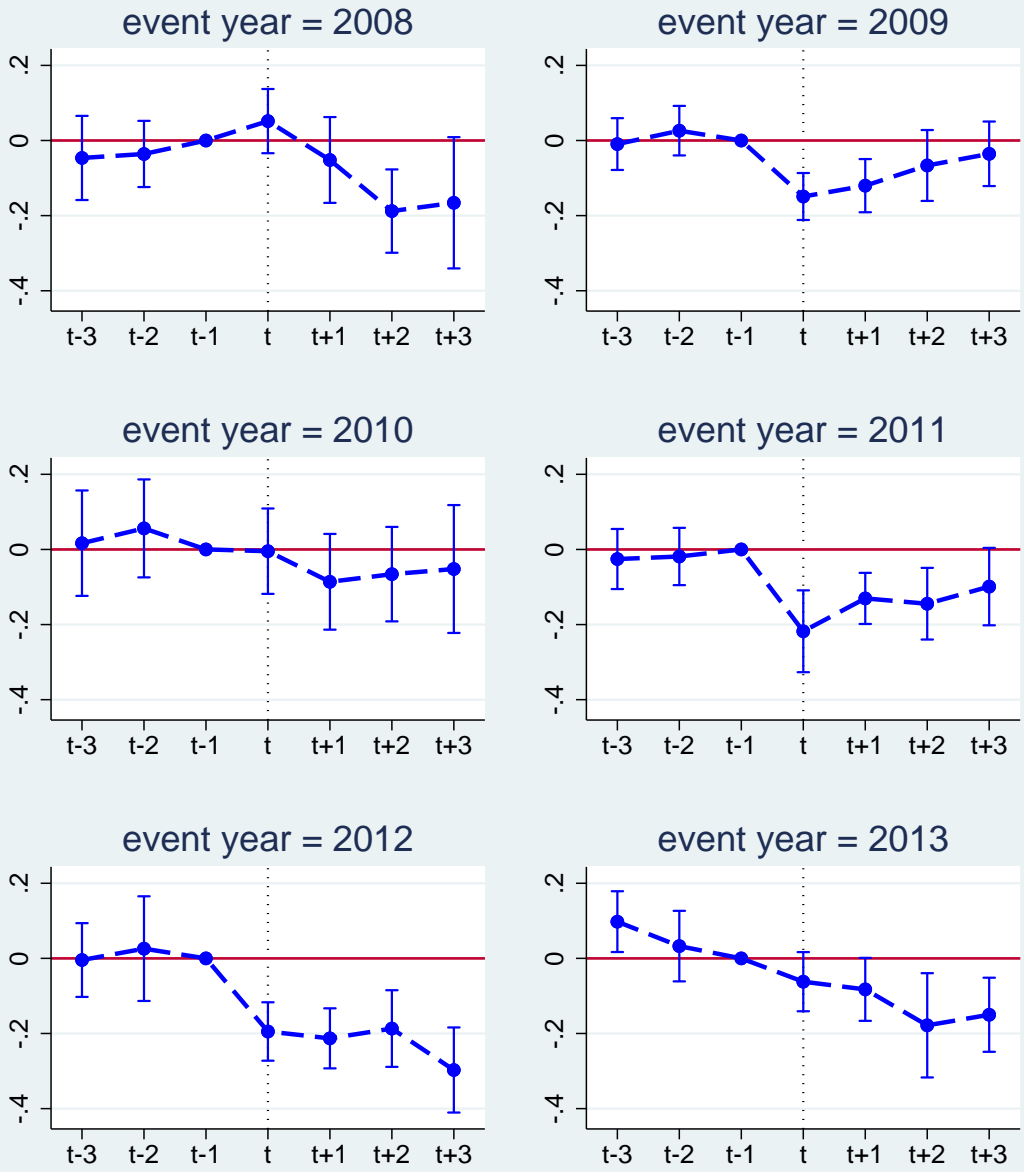
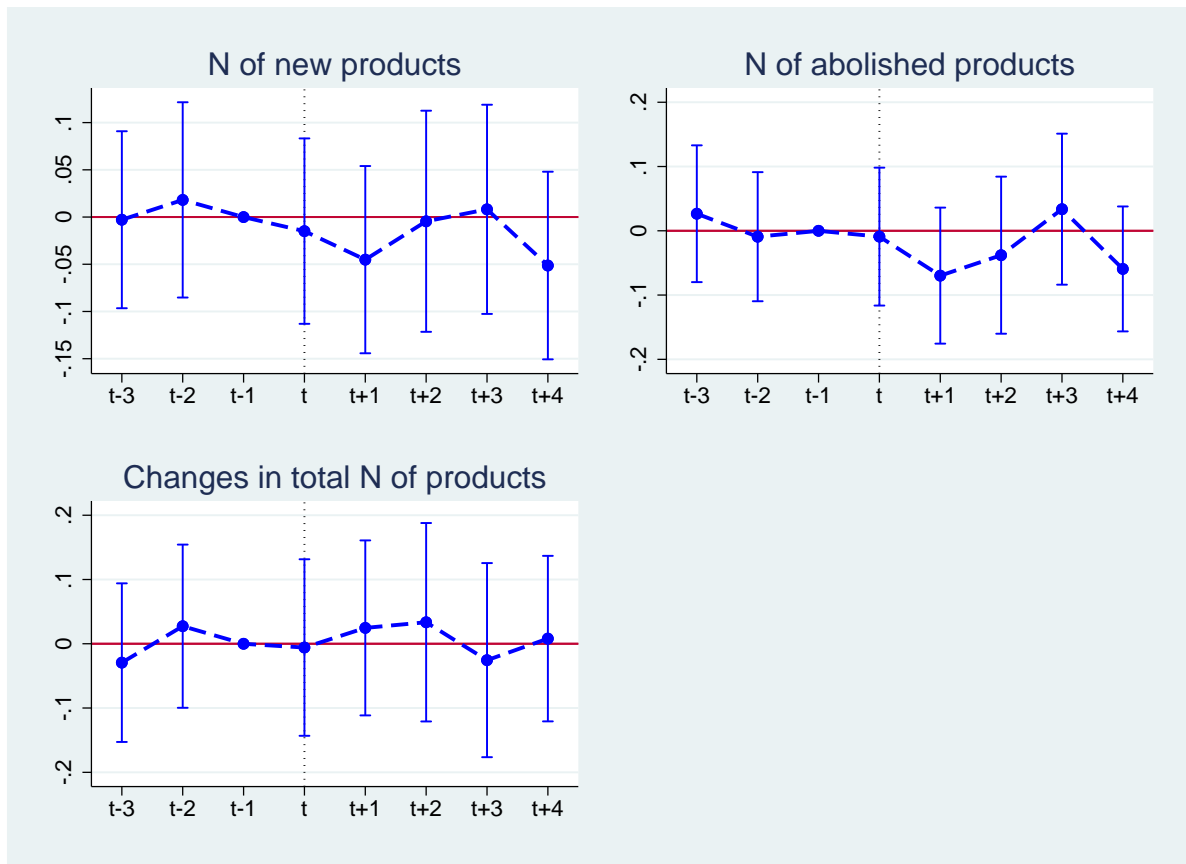**Figure 2: Exogeneity of Layoff Announcements by Event Year**

Note: Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (2)). All models control for plant fixed effects and industry-specific and region-specific linear trends. The models are estimated on stacked event-by-event data sets, separately for each event year. Spikes indicate 95% confidence interval.
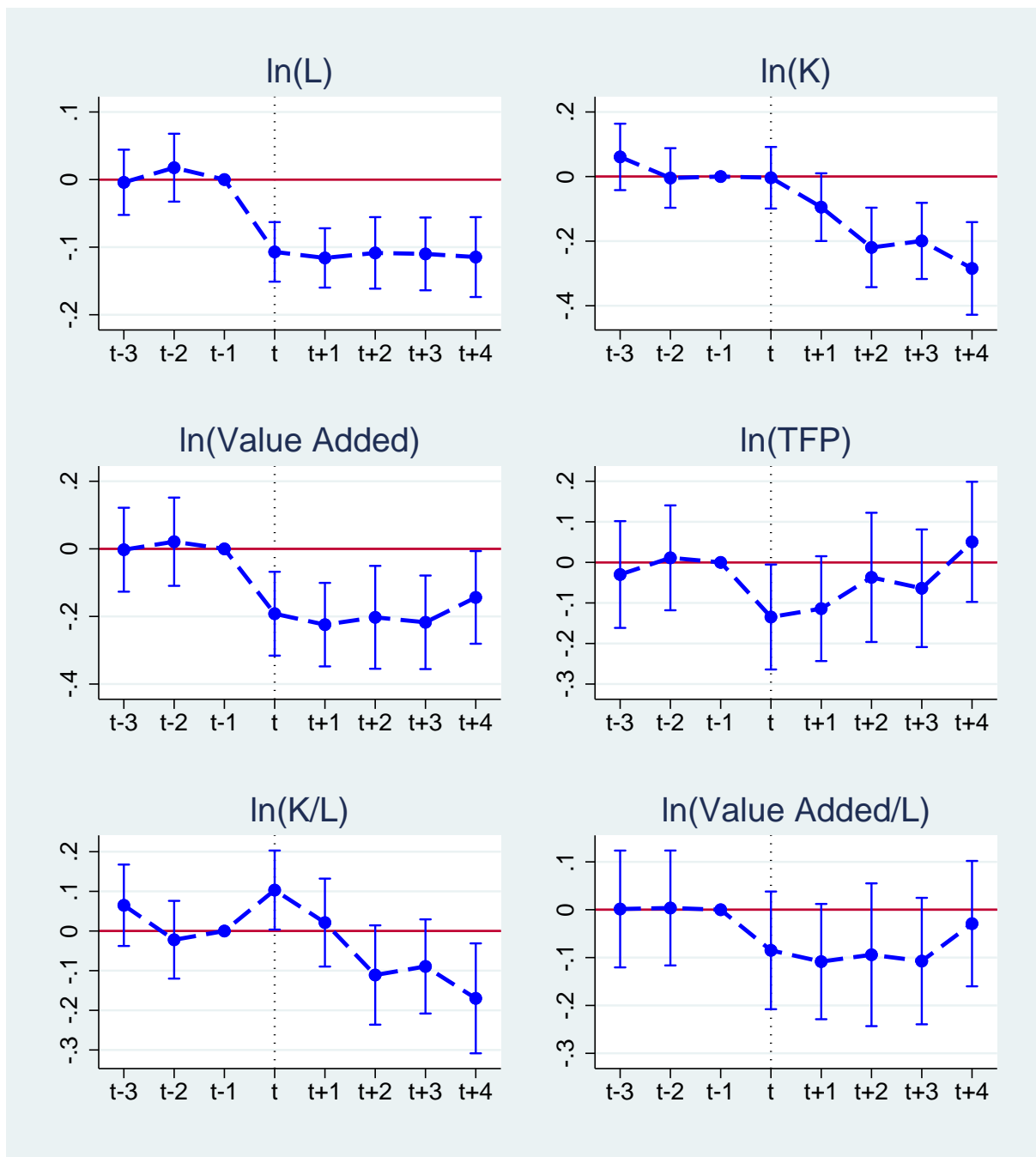
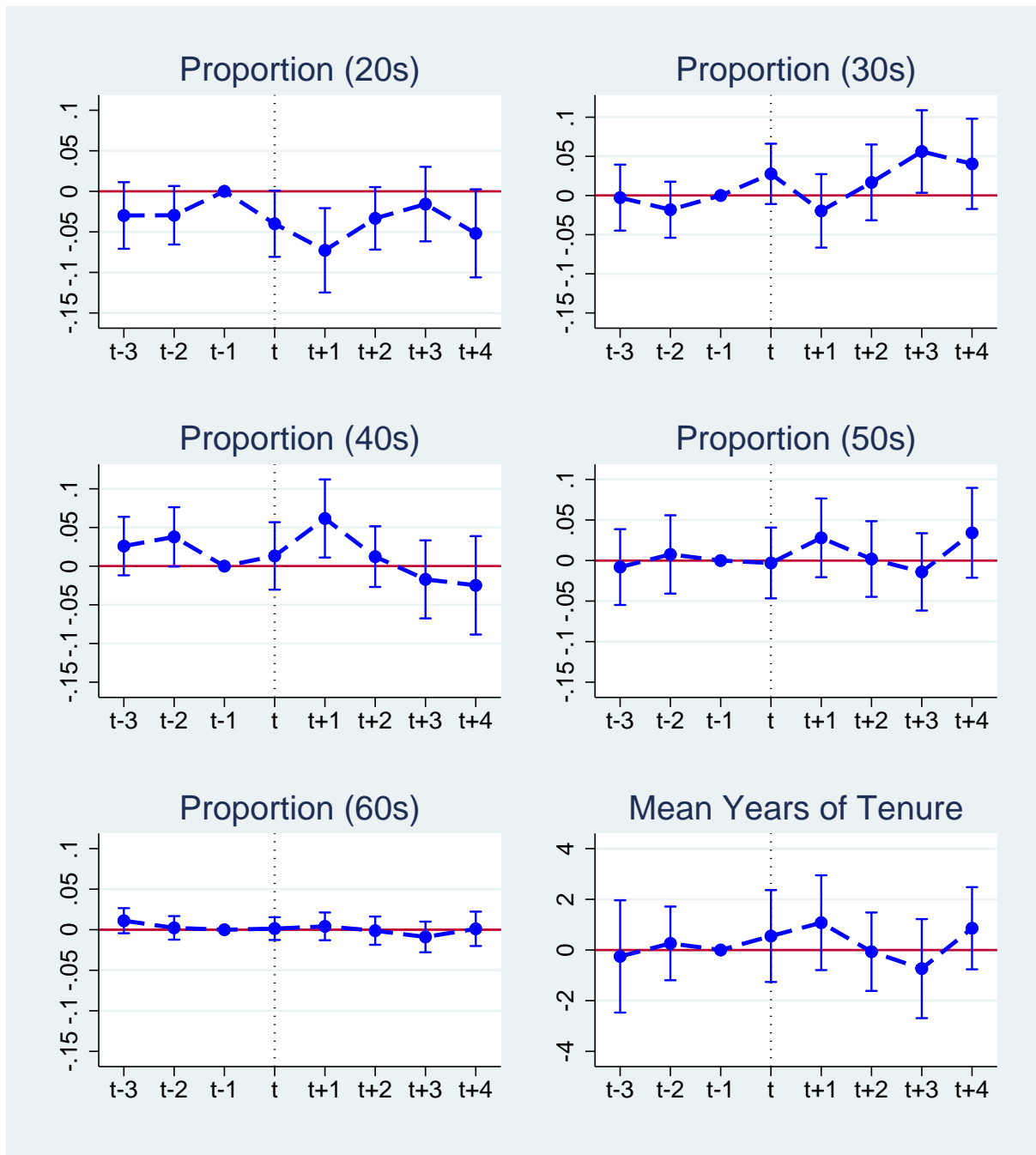**Figure 3: Impacts on Internal Resource Allocation and Outcomes**

Note: Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (3)). All models control for plant fixed effects, event-specific dummies to indicate time periods, event-and-industry-specific linear trends, and event-and-region-specific linear trends. The models are estimated on stacked event-by-event data between 2008 and 2012 (N = 1,529,854). Spikes indicate 95% confidence interval.
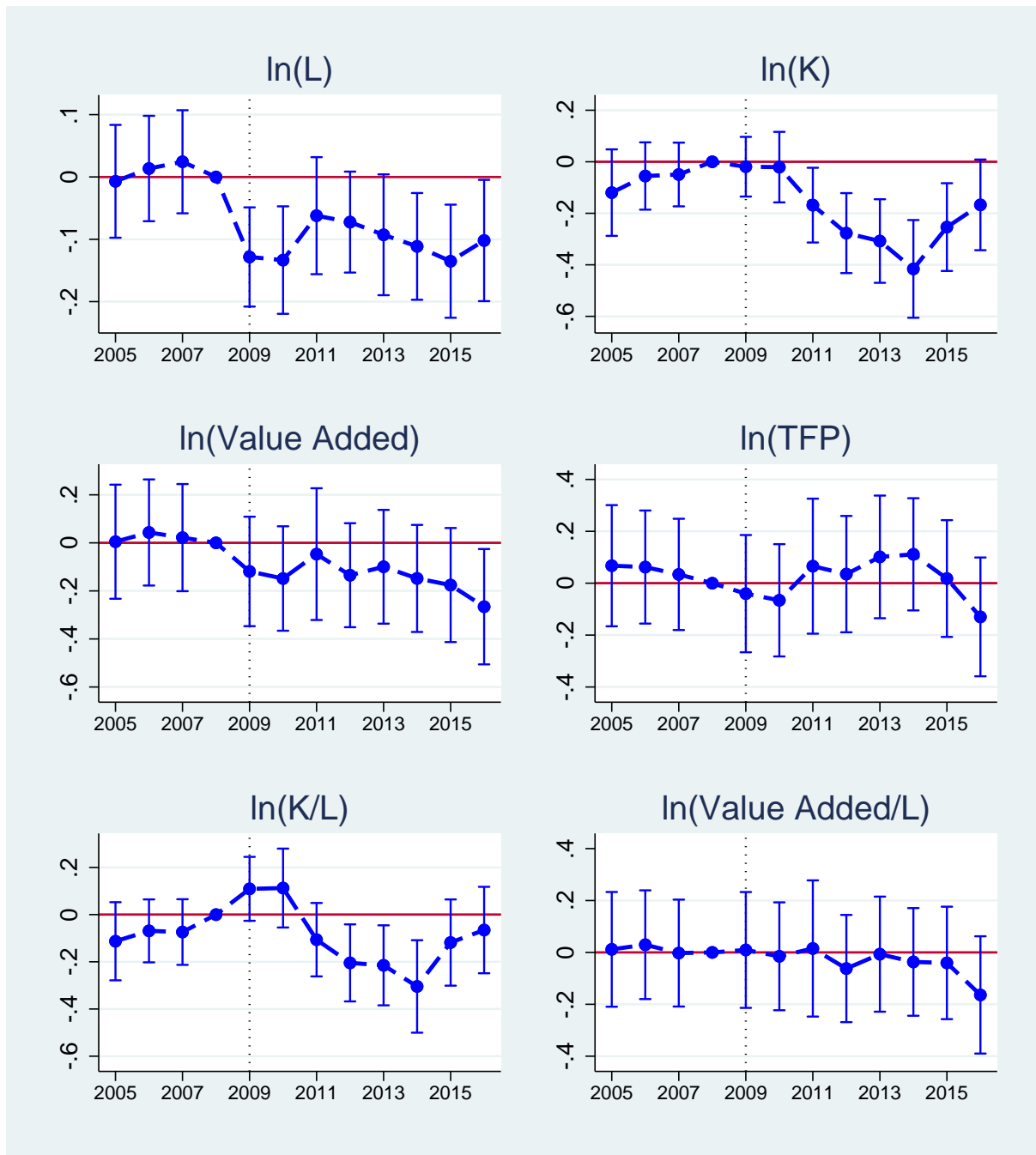
Figure 4: Impacts on Product Creations and Destructions

Note:. Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (3)). All models control for plant fixed effects, event-specific dummies to indicate time periods, event-and-industry-specific linear trends, and event-and-region-specific linear trends.The models are estimated on stacked event-by-event data between 2008 and 2012 (N = 1,529,854). Spikes indicate 95% confidence interval.
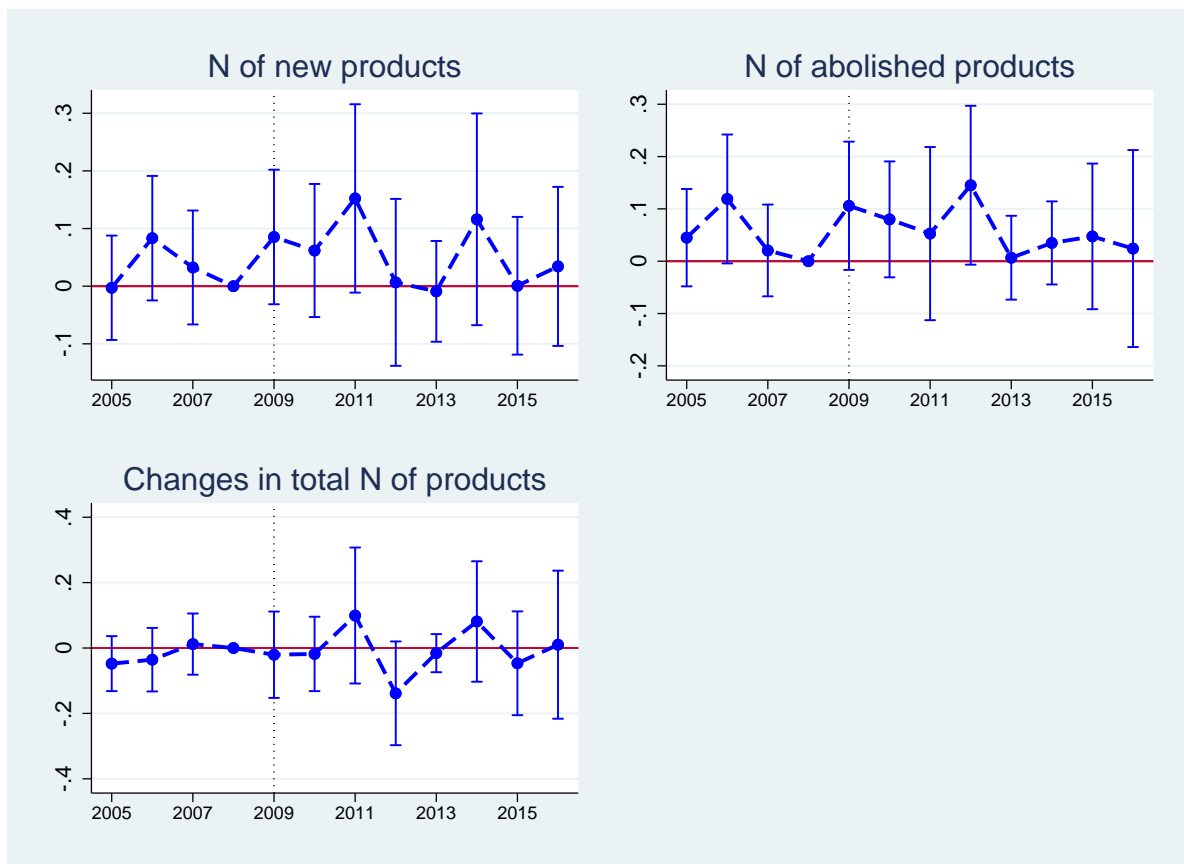
Figure 5: Impacts on Age Composition of Employees (sub-sample)

Note: Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (3)). All models control for plant fixed effects, event-specific dummies to indicate time periods, event-and-industry-specific linear trends, and event-and-region-specific linear trends. The models are estimated on stacked event-by-event data between 2008 and 2010 for those observations with age information from the Basic Survey on Wage Structure (Japanese Ministry of Labour, Health, and Welfare). N = 63,839. Spikes indicate 95% confidence interval.

Appendix Figure 1: Longer-term Impacts on Internal Resource Allocation and Outcomes (Event year = 2009 Only)

Note: Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (2)). All models control for plant fixed effects, dummies to indicate time periods, industry-specific linear trends, and region-specific linear trends. The models are estimated on stacked event-by-event data in 2009 (N = 466,526). Spikes indicate 95% confidence interval.

Appendix Figure 2: Longer-term Impacts on Product Creations and Destructions (Event year = 2009 Only)

Note: Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (2)). All models control for plant fixed effects, dummies to indicate time periods, industry-specific linear trends, and region-specific linear trends. The models are estimated on stacked event-by-event data in 2009 (N = 466,526). Spikes indicate 95% confidence interval.
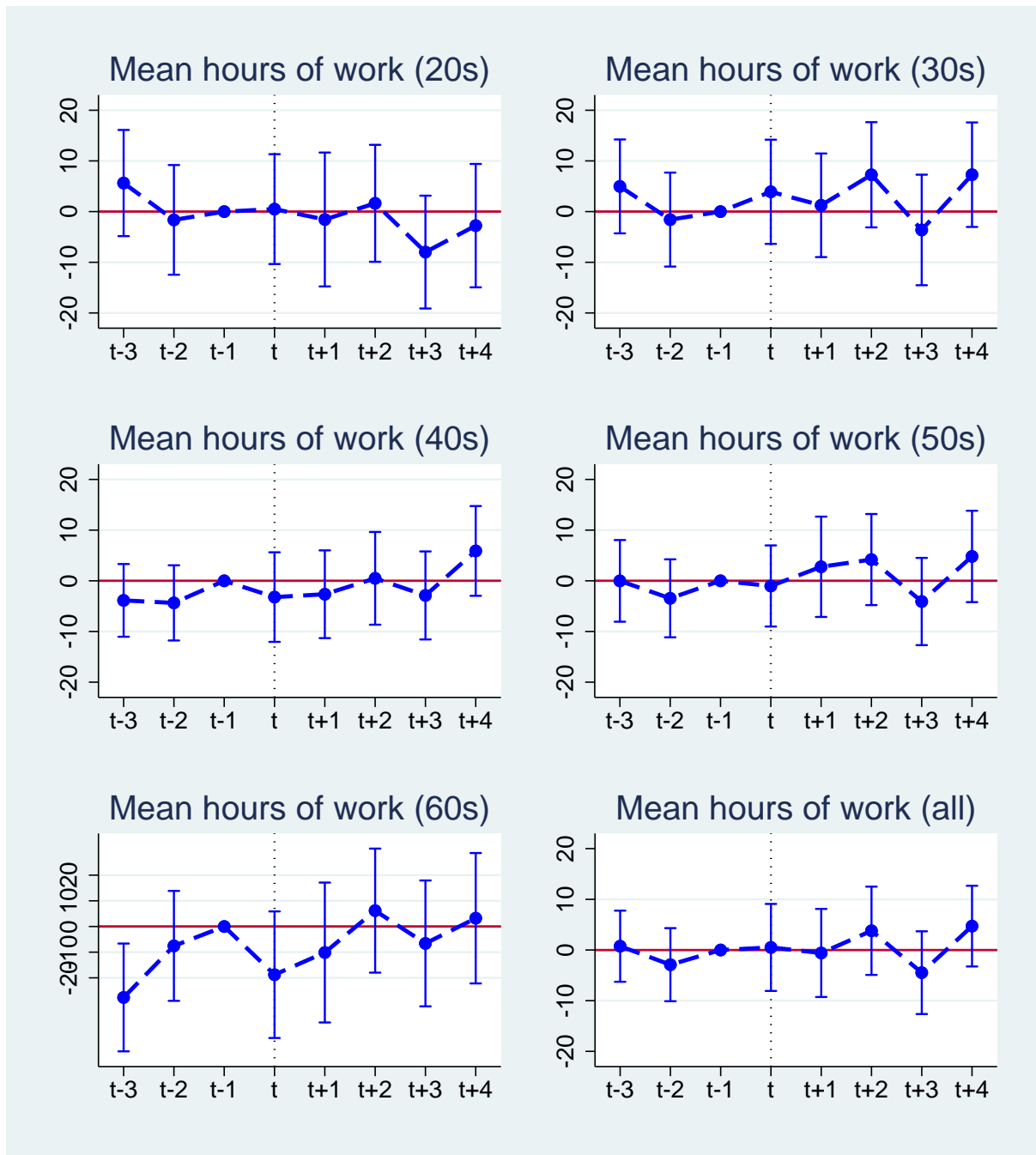
Appendix Figure 3: Impact on New Graduate Recruitment

Note: Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (3)). All models control for plant fixed effects, dummies to indicate time periods, industry-specific linear trends, and region-specific linear trends. The models are estimated on stacked event-by-event data between 2008 and 2010 for those observations with age, bonus, and hours of work information from the Basic Survey on Wage Structure (Japanese Ministry of Labour, Health, and Welfare).N = 63,833. Spikes indicate 95% confidence interval.
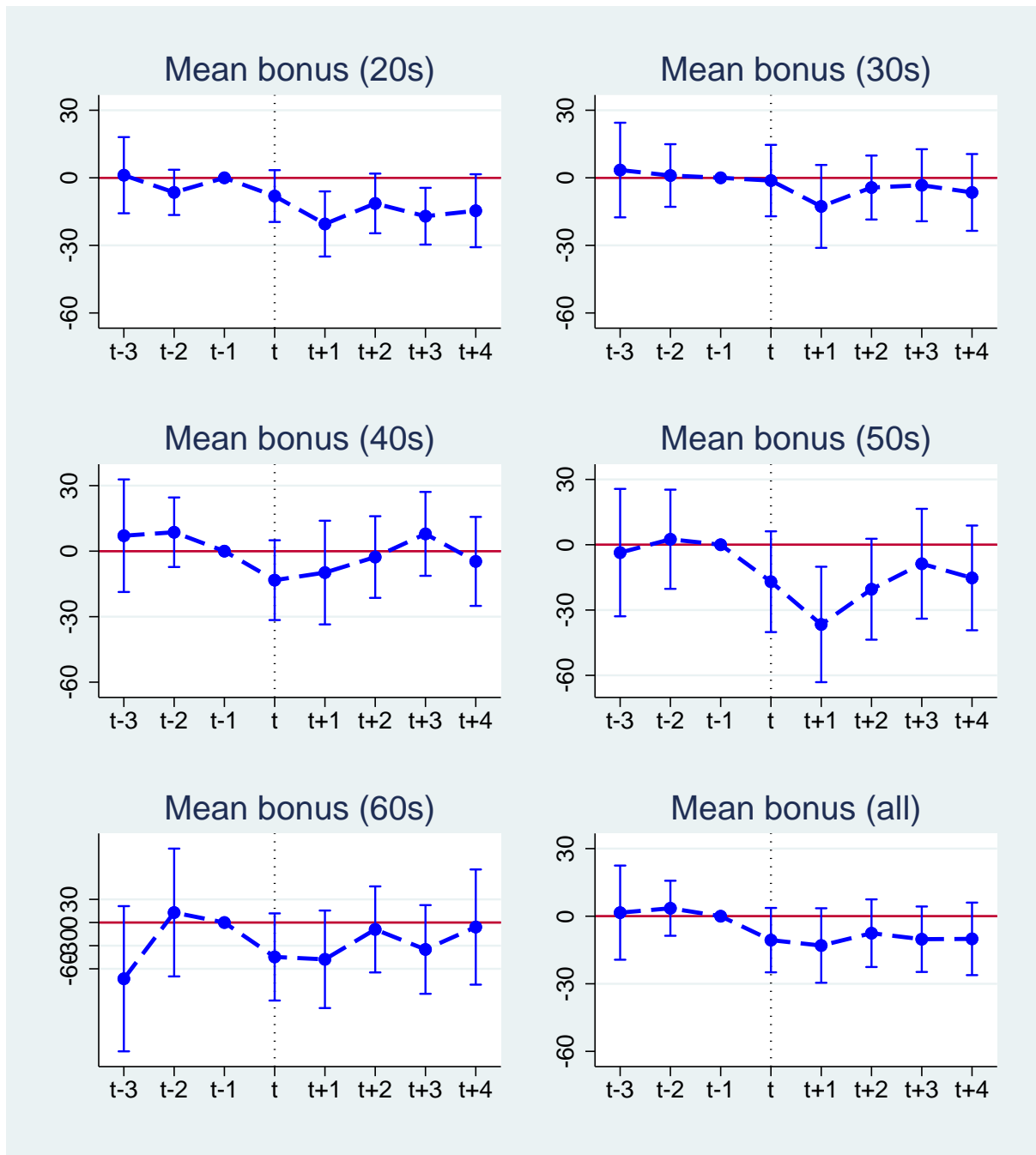
Appendix Figure 4: Impact on Mean Annual Bonus (in 10000 JPY $\approx$ \$90)

Note: Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (3)). All models control for plant fixed effects, dummies to indicate time periods, industry-specific linear trends, and region-specific linear trends. The models are estimated on stacked event-by-event data between 2008 and 2010 for those observations with age, bonus, and hours of work information from the Basic Survey on Wage Structure (Japanese Ministry of Labour, Health, and Welfare). Spikes indicate 95% confidence interval. "Mean bonus" indicates the mean annual bonus in the previous survey year.

Appendix Figure 5: Impact on Mean Monthly Hours of Work

Note: Each graph plots the estimated impact of layoff announcement at each time period (e.g., γ_s in equation (3)). All models control for plant fixed effects, dummies to indicate time periods, industry-specific linear trends, and region-specific linear trends. The models are estimated on stacked event-by-event data between 2008 and 2010 for those observations with age, bonus, and hours of work information from the Basic Survey on Wage Structure (Japanese Ministry of Labour, Health, and Welfare).Spikes indicate 95% confidence interval.

Appendix Table 1: Impacts on Long-term Attrition (Odds Ratio)

Event year (h)	(1) 2008	(2) 2009	(3) 2010	(4) 2011	(5) 2012
Layoff announcement	1.059	0.655	0.277	1.381	0.477
	(0.622)	(0.249)	(0.285)	(0.787)	(0.297)
N	41,831	39,269	38,882	35,875	35,330

Note: Dependent variable is an attrition dummy variable which takes one if the plant is never observed after three years from the event year. Each cell presents odds ratio estimated from a logistic model. All models control for industry and region dummies. The models are estimated on the stacked event-by-event data, separately for each event year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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