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Using Managers' Expectations for Ex-ante Policy Evaluation: Evidence from the COVID-19 Crisis*

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Abstract

Evaluation of the impacts of government policies during an economic crisis is often delayed until the outcomes are realized. Policies can be better guided if they can be evaluated amid a crisis, before the realization of outcomes. This study examines whether survey data on the expectations of small business managers can help evaluate two high-stake subsidies for firms amid the COVID-19 crisis in Japan, namely, Subsidy Program for Sustaining Businesses (SPSB) and Employment Adjustment Subsidy (EAS). We evaluate the accuracy of managers' expectations, estimate the impact of subsidies on the expected firm survival, and compare it with the estimated impact on realized survival. We find that the managers' expectations on their future sales, survival rate, and the possibility of receiving these subsidies predict the realized outcomes, although they were highly pessimistic about their survival rates. We find that the estimated impacts of the SPSB on the expected survival rates have the same sign as the estimated impact on the realized survival rates, but the size is more than twice because of the pessimism on survival. The estimated impacts of the EAS are both insignificant. Therefore, although its impact may be overestimated, managers' expectations are useful for selecting an effective policy.

Keywords: Firm forecast; Policy evaluation; Small business; COVID-19; Subsidies.
JEL Codes: D80; E66; L50; H20.

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1 Introduction

The evaluation of the impacts of government policies during an economic crisis is often delayed until the outcomes are realized. Policies are better guided if policies are evaluated before the realization of outcomes. One possible way is to use data that correlate with future economic outcomes like current expectations of economic agents, such as the firm's managers, for future business outcomes. If the managers surveyed can accurately predict their business trends, they may convey useful information about the policies' effects. For example, we can refer to business sentiment surveys, such as PMI (Purchasing Managers' Index), OECD Business Confidence index (BCI), the University of Michigan's consumer sentiment in the United States, and Nichigin Tankan in Japan, or initiate a survey to collect this information.[1]

This study examines whether survey data on firm managers' expectations can be used to guide policy amid a crisis. This issue is addressed using panel survey data on small business managers, conducted by the authors at four time points during the COVID-19 crisis in Japan: May 2020, July 2020, November 2020, and February 2021. The surveys focus on small businesses that are most vulnerable to economic crises. The surveys elicit expectations about their business performance, pandemics, and policies, as well as realization of the business performance.

Using this survey data, we first examine how expectations are tied to the realizations. Then, we compare the expected and realized impacts of the government policies using the expected and realized economic outcomes. Specifically, using the regression discontinuity design (RDD), we evaluate the impacts of two subsidy programs, the Subsidy Program for Sustaining Businesses (SPSB) and the Employment Adjustment Subsidy (EAS), on the ex-ante subjective probability of closing the business and the ex-post actual business closure, and compared the results. In Kawaguchi et al. (2021), we used the survey conducted in May 2020 on small business managers and showed that the expectations for receiving the SPSB increased the manager's expectation for surviving the COVID-19 pandemic, but that for receiving the EAS did not. In this study, we use the realized outcomes and subsidies instead of the expected outcomes and subsidies.

The accuracy of using managers' expectations is a concern because increasing empirical studies document the inaccuracy and biases of firm decision makers' forecasts about own firm performance (Bachmann and Elstner, 2015; Gennaioli et al., 2016; Altig et al., 2020). Therefore, we first evaluate the accuracy of managers' expectations. We follow Altig et

[1] In Kawaguchi et al. (2021), we used a survey on small business managers' expectations to evaluate subsidy policies.

al. (2020)'s approach to study the strength of the correlation between managers' expectations and realized outcomes. We find that managers' expectations on year-on-year quarterly sales growth rates are strongly correlated with their realization, even during the pandemic. The managers' expectation of survival rate is also highly predictive of the realized survival rates. However, managers are overly pessimistic. Even managers who answered there was no chance of survival in 2020 stay in the market until the end of 2020 with a probability of more than 90%. The managers also correctly predict whether they can receive subsidies. The expectation for the SPSB was highly accurate, possibly because of the simplicity and transparency of the eligibility criteria.

Next, we estimate the effects of subsidies on firms' expected and actual survival rates and compare the ex-ante policy evaluation using managers' expectations and the ex-post evaluation using realized business outcomes. We focus on two large-scale subsidies: SPSB and EAS. The SPSB is a lump-sum transfer and the EAS compensates for part of the leave allowance. We exploit a discontinuity in the eligibility criterion of each subsidy scheme to estimate the causal impacts. We find that receiving JPY 1 million of the SPSB increases the subjective survival probability as of July and November by 10.5 and 18.1 percentage points, respectively. The estimated magnitude is consistent with the result in Kawaguchi et al. (2021), who used the expectation of receiving the subsidy instead of the received amount as the treatment variable. We find that the ex-ante and ex-post policy evaluations of the SPSB showed statistically significant effects of the same sign, but the ex-ante policy evaluation overestimates the ex-post policy evaluation's outcomes. The effects of the subsidy received by July and November on the actual survival are 4.2% and 5.1%, respectively.

In contrast, the EAS was found to be ineffective for both ex-ante and ex-post evaluation. Because the evidence of short-time work compensation is mixed (Balleer et al., 2016; Abraham and Houseman, 2014; Aricò and Stein, 2012; Arranz et al., 2018; Kato and Kodama, 2021), the prior prediction of which subsidies would be more effective in helping small businesses were unclear. The ex-ante policy evaluation using managers' expectations could successfully predict this result. Thus, our analysis shows that managers' expectations are useful for selecting an effective policy, although its impact can be overestimated.

We also replicated the analysis by replacing the amount of subsidy received with the subjective probability of receiving the subsidy and found that the estimated effects of the SPSB was unchanged. This could be because the anticipation for the receipt of SPSB was accurate due to the simplicity and transparency of the eligibility criteria. Thus, the simple and transparency rule does not only reduce the uncertainty for managers but also helps policy makers to improve the accuracy of ex-ante policy evaluation using managers' expectations.

This study is related to several branches of literature. First is the literature on empirical methods to evaluate policies in real-time, such as stated preference methods and conjoint experiments, which ask respondents about their preferences over hypothetical policies. However, these methods face criticism on their credibility and biases (Diamond and Hausman, 1994) and questioned on whether the answers in non-incentivized hypothetical conditions reflect true preferences (List, 2001; Hainmueller et al., 2015). Furthermore, while these survey designs are useful for understanding the preferences of respondents over different policy designs, they are typically not suitable for evaluating the impacts of policies on economic outcomes. An alternative approach we explore is to ask expectations about economic outcomes rather than the preference for a policy and infer the effect of the policy on the expected outcomes. More specifically, our approach is to use the expected outcomes of individuals in place of the realized counterpart, employing standard empirical methods for causal identification such as regression discontinuity design.

Similarly, this paper is connected to the classic literature on the use of firms' reports on private information for designing regulations Weitzman (1978); Loeb and Magat (1979); Sappington (1982); Baron and Myerson (1982); Laffont and Tirole (1986); Shleifer (1985). The literature mainly focuses on the ways to elicit true private information, considering an industry with one or a few large firms. Contrary, we are not concerned with strategic misreports because we survey a large number of small firms, where misreporting by one manager would not affect the policy selection.

Second, this study builds on the recent empirical literature that examines the accuracy of firm managers' quantitative forecasts. Coibion et al. (2018) documented a large dispersion of macroeconomic forecasts across firms and attributed this to firms' inattention to recent macroeconomic conditions. Studies using firms' forecasts regarding own performance also showed large forecasting errors (Bachmann and Elstner, 2015; Massenot and Pettinicchi, 2018; Bloom et al., 2020), and Bloom et al. (2020) documented that these forecasts could have been improved if firms just accurately reported their recent performance. Bachmann and Elstner (2015) also documented that approximately one-third of firms systematically over- or underpredict their future production. In contrast, some studies indicated that firms' forecasts contain meaningful information about future outcomes. Barrero (2021) showed that the average forecast errors about the own firm's performance are approximately zero. Gennaioli et al. (2016) and Altig et al. (2020) documented that firms' expectations of their own business are frequently updated and strongly correlated with the realized outcomes. While these studies are suggestive, it is unclear whether firms' expectations could be used for ex-ante policy evaluations.

Third, this study is related to the literature on the impacts of COVID-19-related policies. Large-scale social anticontagion policies, such as the lockdown of cities, temporary closure of businesses and schools, and prohibition of group gatherings, have been implemented worldwide to contain the spread of the infection (Hsiang et al., 2020; Flaxman et al., 2020). Meanwhile, governments also have implemented economic stimulus policies, including cash transfer, bailouts, and subsidies (Cororaton and Rosen, 2020; Meier and Smith, 2020; Elenev et al., 2021; Kaneda et al., 2021). Analyses on COVID-19-related policies often use data on real-time economy based on high-frequency data or real-time survey data (Adams-Prassl et al., 2020; Chetty et al., 2020; Lewis et al., 2020). These studies have used the realized outcomes and performed ex-post policy evaluation. We use the outcomes expected by business managers to perform ex-ante policy evaluation, in addition to the ex-post policy evaluation using realized outcomes, and compare the ex-ante and ex-post policy evaluations.

Fourth, this study is connected to the literature on COVID-19 and small and medium-sized enterprises (SMEs). SMEs have been severely affected by the first wave of the COVID-19 crisis in Japan (Yamori and Aizawa, 2021). Effects of the COVID-19 pandemic on SMEs' business performance have been analyzed worldwide since early 2020. For example, Bartik et al. (2020) documented the impacts of the COVID-19 crisis on small businesses in the United States, showing a positive association between the expected duration of the crisis and business closure. Bloom et al. (2021) found significant negative sales impact based on survey data on an opt-in panel of approximately 2,500 US small businesses. Gourinchas et al. (2020) showed a large impact of the COVID-19 pandemic on SMEs' failure in 17 countries. They also showed that, in the absence of government support, the SME failure rate increases 9.84 percentage points compared to a counterfactual non-COVID year. Other studies consistent with this literature examined how the Paycheck Protection Program (PPP), which offered guaranteed loans to small businesses in the United States, worked (Hubbard and Strain, 2020; Fairlie and Fossen, 2021; Katare et al., 2021). In the case of Japan, Kawaguchi et al. (2021) and Miyakawa et al. (2021) estimated the effects of subsidies on the survival of small businesses. As SMEs are more vulnerable to the pandemic, they tend to exit from the market. Belghitar et al. (2021) investigated the impact of COVID-19 on firm survival using data on the UK SMEs. Bartlett and Morse (2020) used firm-level data in Oakland to show that the success of PPP applications increases medium-run survival probability by 20.5% for small business.

This study has been presented as follows. The following sections describe the data used and subsequently evaluate managers' expectations and expectation updating in Section 3. Section 4 presents the comparative results of ex-ante and ex-post policy evaluations, followed by concluding remarks in Section 5.

2 Data

2.1 Survey

We conducted a panel survey on managers of small businesses during the COVID-19 pandemic at the following four points in time: May 2020, under the first declaration of the nationwide emergency; July 2020, after the lifting of the emergency declaration and the early beginning of the second wave of infection; November 2020, when the infection situation was relatively calm; and February 2021, amid the second state of emergency in many regions due to the rapid spread of the infection. Figure 1 shows the survey timings along with the transition of the number of infections in Japan.

The sampling frame consists of 28,169 individuals who were registered as top managers, self-employed, or freelancers at one of the largest market research agencies in Japan. Among them, we targeted managers of small businesses with less than 20 employees at the end of 2019, because they were most vulnerable to the pandemic and not sufficiently covered in the government statistics.

These surveys asked managers of small businesses about the firm's business, including monthly realized sales growth compared to the previous year, quarterly realized employment and investment, and subjective probability of survival at the end of the year (2020 in the first three surveys and 2021 in the last survey). The survey also asked whether they expected to receive the subsidies offered by the central and local governments in the coming quarters. In all surveys, we asked the expected values of sales growth, employment, and investment in the forthcoming three quarters from the survey dates. The survey also asked about the firm's expectations of COVID-19-related events: for example, when would the COVID-19 outbreak in Japan be contained, that is, when the number of daily new infections would drop to zero for the first time in Japan? When would mass vaccination against the virus become available in Japan? How likely is it that Tokyo Olympics would be held in 2021? Section A.1 in the Appendix presents the translated sentences of the relevant questions.

In the first survey in May 2020 (hereafter the May survey), we sent questionnaires to all 28,169 managers. We collected responses from 12,364 respondents and used 6,466 managers' responses based on the number of employees and response quality for this study. The survey period was from May 8 to May 17, 2020.

In the second survey in July 2020 (the July survey), we sent questionnaires to all sample used for analysis in the May survey (6,466 sample), as well as to those who met the criteria of occupation and company size through a pre-survey (4,381 sample). Among 8,866 respondents, we used a sample of 7,595 managers after data cleaning. The survey period was from July 22 to July 30, 2020.

In the third survey in November 2020 (the November survey), we sent questionnaires to all panel samples obtained from the July survey (7,595 sample), as well as respondents in the November pre-survey and the May survey, and non-respondents of the July survey. Among 7,732 responses collected, we had 6,746 individuals after data cleaning. The survey period was from November 2 to November 9, 2020.

A few days before the fourth survey in February 2021 (the February survey), we sent a short questionnaire (the February pre-survey) to all 28,169 managers in the original sampling frame of the May survey to ask whether they closed business in the year 2020, and if so when. Our survey targeted individuals rather than business entities; therefore, the responses are not likely to be mechanically influenced by business closures, although there could be a psychological effect leading to non-response as we investigate later. We sent the February survey to managers who responded the pre-survey in February, and respondents in either of the May, July, or November surveys. Among the 9,227 respondents, we had 7,535 samples after data cleaning.

A lengthier questionnaire for the February survey was then sent to all who responded to the pre-survey and who had responded at least once before the November survey. Thus, 5,480 managers remained on the panel sample. The survey period was from February 5 to February 12 in 2021. Section A.2 in the Appendix provides further details about the survey design.

In all surveys, through data validation checks, we excluded respondents who gave inconsistent or unrealistic answers or were not top managers of small businesses. To balance the distribution of industry classification and employment size with the national statistics, we weighted each observation according to the number of small businesses in the corresponding industry and employment size in the Economic Census. In the following sections, we only report the weighted results. Section A.3 in the Appendix provides details about the data cleaning process.

2.2 Summary Statistics

Table 1 shows that the average number of employees, excluding top managers him/herself was 3.6 at the end of 2019 and reduced until Q3, 2020. In total, 29% of our sample engaged in investment in Q1 2020, while 38%, 36%, and 37% invested in Q2, Q3, and Q4, respectively. Business-to-Consumer (B-to-C) service, Business-to-Business (B-to-B) service, and non-service industries consisted of 50%, 23%, and 27%, respectively. The average age of managers was 56.7 years, and male managers constituted 91% of our sample. Year-on-year sales growth in January 2020 was -0.36%, while after the outbreak of the pandemic, it ranged

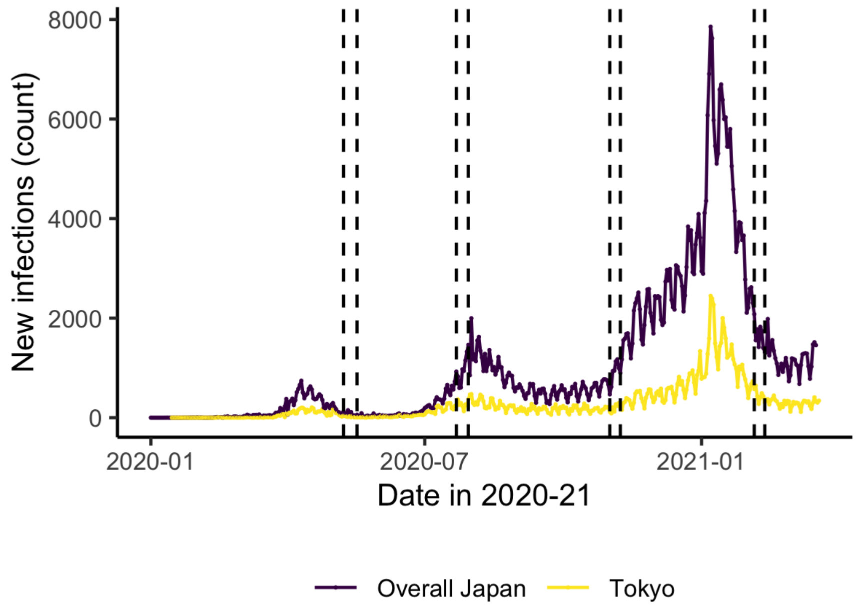


Figure 1: Survey timing and infections
Note: Dotted lines denote the survey periods: May, July, November, and February. While purple line shows the transition of number of infections in entire Japan, yellow one shows that in Tokyo.

from -16.2% to -2.9%. Figure 2 shows the statistics by sector: B-to-C service, B-to-B service, and non-service. The decline in year-on-year sales growth were large, especially in B-to-C service. Table 1 also shows that the subjective probability of survival by the end of 2020 is, on average, 84–87%.

Among the respondents to the February pre-survey (7,027), 101 closed the business by the end of December 2020.[2] Therefore, the business closure rate from May 2020 to December 2020 in our sample is 1.44%. If we simply extrapolate this value, the annual closure rate is around 2.16%. This number of relatively small but comparable to national level statistics. According to the Small and Medium Enterprise Agency (2022), the annual closure rate of establishments in Japan, calculated from the employment insurance statistics, is 3.4% in 2019. It should be noted that this 3.4% is establishment-level statistics and not firm-level statistics, therefore direct comparison may require caution.

2.3 Attrition Problem

Some individuals opted out during the follow-up surveys. If the attrition is not at random, it may induce a bias in our analysis. The non-response to the February pre-survey, which is

[2]This number includes 19 respondents who closed business since May 2020 but did not answer the question of when the business was closed.

Table 1: Summary statistics: Panel sample

	count	mean	sd	min	max
Number of employees in Q4 2019	5480	3.56	4.05	0	19
Number of employees in Q1 2020	5480	3.35	3.92	0	23
Number of employees in Q2 2020	5480	3.14	3.95	0	22
Number of employees in Q3 2020	5480	3.05	3.96	0	27
Number of employees in Q4 2020	5480	3.16	4.08	0	26
Realized investment in Q1 2020 is positive	4412	0.29	0.45	0	1
Realized investment in Q2 2020 is positive	4353	0.38	0.49	0	1
Realized investment in Q3 2020 is positive	5480	0.36	0.48	0	1
Realized investment in Q4 2020 is positive	5480	0.37	0.48	0	1
Realized sales growth in Jan 2020	5097	-0.36	25.13	-100	200
Realized sales growth in Feb 2020	5097	-2.89	27.01	-100	180
Realized sales growth in Mar 2020	5097	-8.90	33.61	-100	157
Realized sales growth in Apr 2020	5097	-16.17	40.24	-100	150
Realized sales growth in May 2020	2101	-15.38	34.04	-100	100
Realized sales growth in Jun 2020	2101	-11.54	29.78	-100	100
Realized sales growth in Jul 2020	3825	-9.74	27.18	-100	128
Realized sales growth in Aug 2020	3825	-8.52	26.57	-100	170
Realized sales growth in Sep 2020	3825	-7.61	24.56	-100	100
Realized sales growth in Oct 2020	4366	-7.50	26.25	-100	200
Realized sales growth in Nov 2020	4366	-7.65	26.75	-100	200
Realized sales growth in Dec 2020	4366	-7.97	28.62	-100	200
Realized sales growth in Jan 2021	4366	-9.06	30.91	-100	200
Industry: Business to Consumer service	5480	0.50	0.50	0	1
Industry: Business to Business service	5480	0.23	0.42	0	1
Industry: Non-service	5480	0.27	0.44	0	1
Average age	5480	56.68	9.34	21	89
Male	5480	0.91	0.29	0	1
Prob. of business survival by the end of 2020: May survey	4082	84.73	23.50	0	100
Prob. of business survival by the end of 2020: Jul survey	4353	84.36	23.88	0	100
Prob. of business survival by the end of 2020: Nov survey	5480	87.28	22.88	0	100
Observations	5480				

Note: The observations are weighted to match the number of firms in the Economic Census.

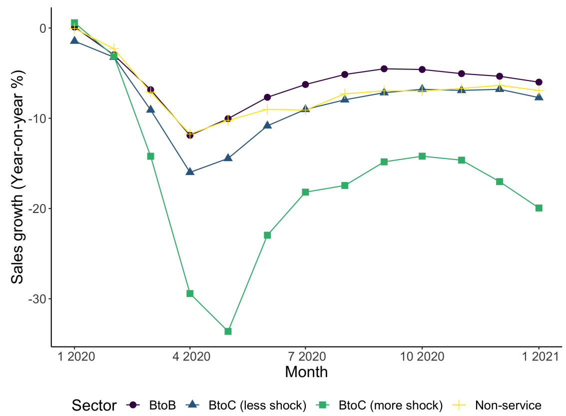


Figure 2: Realized monthly sales growth

Note: This figure shows the average monthly year-on-year sales growth by sectors. Purple, blue, green, and yellow lines denote B-to-B, B-to-C with less face to face, B-to-C with more face to face, and non-service sectors, respectively.

sent to the original sampling frame of 28,169 top managers, could be potentially a problem to our analysis, because we use the response to this pre-survey to measure the actual survival rate.

To examine a possible attrition problem arising from non-response in the February pre-survey, we compare the baseline characteristics of our analysis sample in the July survey between those who answered the February pre-survey and those who did not. Table A4 in the Appendix indicates the results. First, older individuals are more likely to respond, while the difference in response rates by gender is small and insignificant. Second, firm size (measured by sales or capital) does not predict response. Third, the accuracy of the sales forecast, measured by the absolute deviation of the expectation about April-June sales (answered in May) from its realized value (answered in July), is not significantly different across the response and non-response groups. Fourth, subjective probabilities of receiving subsidies (answered in July) do not predict response. Lastly, however, survival expectation (answered in July) is positively correlated with response: individuals who expected the probability of survival as 100% in the July survey were on average 8.1 percentage points more likely to respond, compared to those who expected the survival probability as 0%. This result implies a possibility that individuals who closed the business became less likely to respond to the February pre-survey. Panel (a) of Table A5 in the Appendix shows the basic statistics for the same variables between the response and non-response groups and indicates a similar pattern. Panel (b) compares the compositions of major cities and sectors between the response sample and the non-response group, showing that the shares in this dimension are mostly stable across the samples.

Attrition may lead to an estimation bias when it is correlated with underlining heterogeneity in the treatment effects of the subsidy. For instance, if individuals with large treatment effects are less likely to drop out from the survey compared to those with small treatment effects, the estimates could be upwardly biased. The positive correlation between survival expectation and response suggests this possibility: upon receiving the subsidy, individuals with large treatment effects would become less likely to exit, thus more likely to stay in the survey, compared to individuals with small treatment effects. However, the magnitude of the bias is considered to be small. To illustrate the magnitude, suppose that we have two groups with a large difference in treatment effects of a subsidy on survival rate: 20% for one group and 0% for the other group (this is an exaggeration, because we show later that our estimate of the average effect of the SPSB on survival is around 4%). Assuming that a change in the actual survival rate by 20% corresponds to the change in expected survival probability by 20%, the response rate of individuals with larger treatment effect would be 1.62 (=20% $\times$ 8.1%) percentage points higher compared to the response rate of individuals with smaller treatment effect. Compared to the average follow-up rate (80%), the magnitude of this effect is too small to influence the overall conclusion.

Furthermore, we examined whether the results of ex-ante policy evaluation change when we restrict the sample to those who answered the February pre-survey. As we discuss in Section 4, we find qualitatively the same conclusion on the comparison between ex-ante and ex-post evaluations when we restrict the sample to the balanced panel sample.

2.4 Comparison with External Data

There is a need to examine whether our sample is representative of Japanese small businesses. First, we compare the distribution of our survey data with the Economic Census that covers all Japanese firms (See Table A6). Though the industry distribution of our survey is quite similar to the one in the whole economy, the size of firms surveyed tends to be smaller than the economy as a whole.

Second, we provide benchmarks for assessing the representativeness of the survey respondents in terms of managers' personal demographics. Because there is no government statistics available on the personal attributes of firm top managers, we compared our results to the average age and gender of respondents in other surveys conducted by a credit rating agency and the numbers in the existing literature. The average age of the head of a company in our sample was 56.7 as shown in Table 1, while that in the *Teikoku Data Bank (TDB) database* is around 60 as of 2021 according to the TDB (2022). In addition, our sample includes about 9% female managers, Kodama and Li (2018) presents the average percentage of female top manager, using *Tokyo Shoko Research (TSR) database* in 2015, is about 7 %.

Third, we compared the average realized sales growth of our sample and that of SMEs in other large-scale survey data conducted by *Tokyo Shoko Research* (TSR). Figure A4 in the Appendix shows the same trends of sales growth, but do not necessarily coincide with our sample shown in Figure 2, because the definition of SMEs in the TSR dataset is different.

3 Evaluating Managers' Expectations

In this section, we evaluate the accuracy of the managers' expectations by examining the correlation between the expected and realized outcomes. We replicate some of the analyses in Altig et al. (2020), which studied business managers' expectations about sales growth, to evaluate the accuracy of the expectations during a crisis compared to the normal time. In addition, we also evaluate the forecasts and realization of survival until the end of 2020 and the receipt of subsidies for later studying the effect of subsidy receipts on the firm's survival.

Sales growth Following Altig et al. (2020), we transform the sales growth of a range $[-1, \infty]$ to a range of $[-2, 2]$ by applying a transformation formula of $SaleGr = \frac{2SaleGr}{SaleGr+2}$. Altig et al. (2020) used quarter-on-quarter sales growth, but we use year-on-year quarterly sales growth, which does not require consideration about seasonal variations.

Figure 3 (a) shows the binned plot of the transformed expected and realized sales growth rates. The plot demonstrates a positive correlation between these variables. Table 2 confirms this finding by regressing the realized sales growth rates on the expected sales growth rates. Unconditionally, the correlation is 0.653 and the R-squared is 0.522. As we control for the firm-fixed effects, the correlation drops to 0.093 and the R-squared increases to 0.928. This means that almost half of the variation is between firms. The correlation and the R-squared are unchanged by further controlling for the quarter-fixed effects. The firm managers understand their average sales growth rate and accurately predict some of the firm-quarter specific shocks to sales growth.

In an analysis by Altig et al. (2020), the unconditional correlation is 0.585 and the correlation after controlling for firm-time-fixed effects is 0.477. The unconditional correlation in our survey is comparable to this number, implying that the predictive power of managers' expectations is as high as the normal period. However, the correlation after controlling for the firm-quarter-fixed effects is substantially lower than the number derived by Altig et al. (2020), perhaps because our sample covers only three quarters in 2021, whereas the sample in Altig et al. (2020) covers quarters from October 2014 to October 2019. Therefore, the firm-fixed effects in our survey capture more temporary heterogeneity, which is not captured

Table 2: Correlation of expected and realized sales growth

	(1)	(2)	(3)	(4)
Expected Sales Growth	0.653***	0.648***	0.093***	0.093***
	(0.008)	(0.008)	(0.010)	(0.010)
Num.Obs.	6804	6804	6804	6804
R2	0.522	0.532	0.928	0.933
R2 Adj.	0.522	0.532	0.825	0.837
Quarter FE	NO	YES	NO	YES
Firm FE	NO	NO	YES	YES

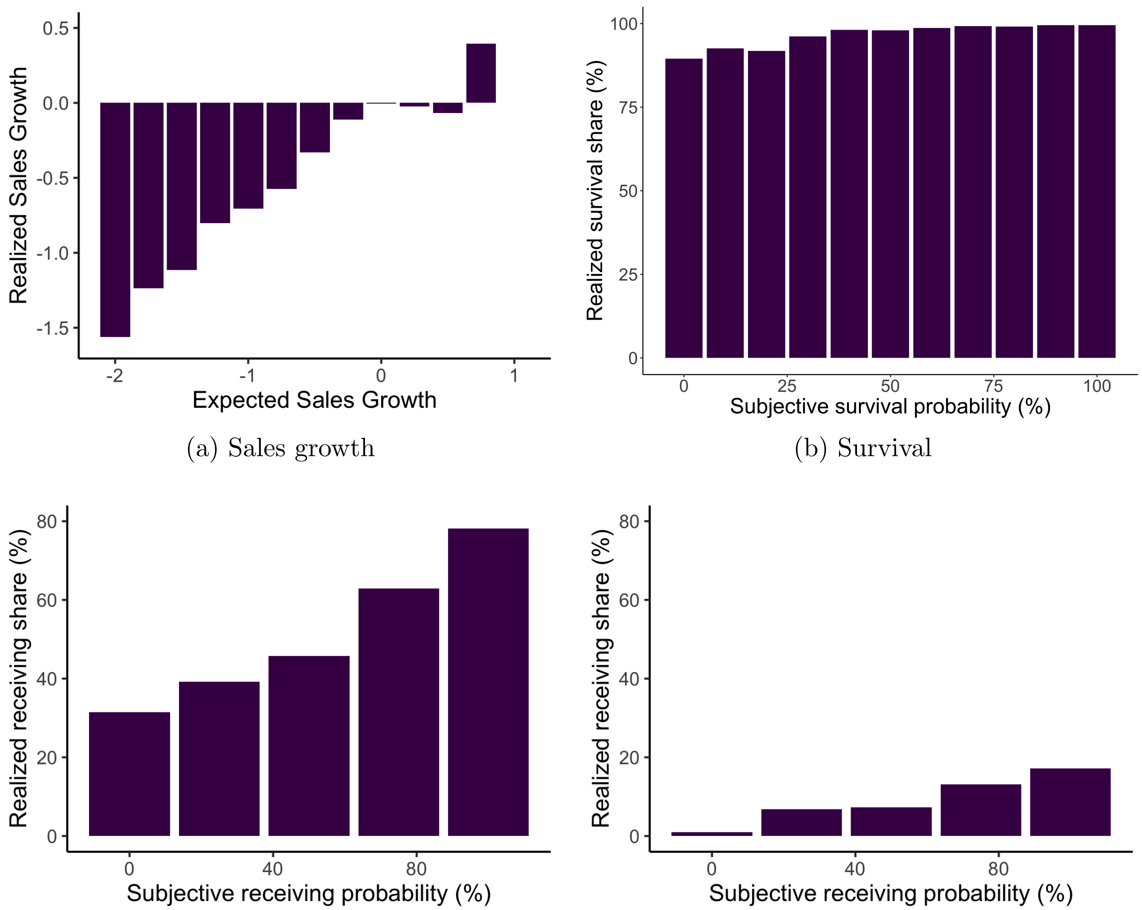
Note: Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

by the firm-fixed effects in Altig et al. (2020). Alternatively, the difference between crisis and normal time may matter.

To explore the features of optimism and pessimism in sales forecasts, we also examine the distribution of sales forecast errors in Appendix section A.4. The sales forecast error is defined by the realization of sales growth subtracted by its forecast made in a prior survey. The forecast errors tended to be left skewed, implying that some managers were overly optimistic.

Another angle to evaluate managers' forecasting ability is to investigate whether managers learn from their past forecast mistakes. When managers update their sales expectations, they should know their recent forecast errors. To evaluate managers' ability to adjust expectations based on their past errors, we examine the relationship between a manager's forecast error on the last quarter's sales growth and the manager's forecast update on the next quarter's sales growth. The result is shown and discussed in Appendix section A.5. In short, we find evidence consistent with the hypothesis that firms tend to update their forecasts by learning from the past forecast errors. In addition, we examine whether this managers' response to the recent forecast error is reasonable or over-extrapolation. If managers over-extrapolate the recent shock to the future, their expectations are unstable. We examine this by following the approaches by Coibion and Gorodnichenko (2015) and Altig et al. (2020). We find that when managers update their expectations, they mildly over-extrapolate the recent news (see Appendix section A.5 for more details).

Survival In addition to sales growth, we measure firms' outcome by the firm's survival, rather than temporary sales fluctuations, because it is often a more important margin for managers of small businesses. Figure 3 (b) compares the managers' average subjective probability of surviving until the end of 2020 and their actual survival rates. Regardless of the



(a) Sales growth

(b) Survival

(c) SPSB

(d) EAS

Figure 3: Accuracy of expectations

Note: Panel (a) shows the relationship between a manager's sales growth expectation for a quarter, forecasted in the preceding quarter, and its realization. Panel (b) shows the relationship between a manager's subjective survival probability, forecasted in a survey wave, and the firm's realized survival indicator. Panel (c)–(d) show the relationship between a manager's subjective probabilities of receiving SPSB (panel (c)) and EAS (panel (d)) in a quarter, forecasted in the preceding quarter, and their realizations. Panel (a) and (c)–(d) use firm-quarter level data, and panel (b) uses firm-wave level data. All panels are binned plots, showing the mean of the variable in the y-axis for each bin of the variable in the x-axis.

survey timing, the subjective survival probability is positively correlated with the actual survival rate. The regression of the survival dummy on the subjective survival probability controlling for survey wave-fixed effects, which includes 22,839 firm-wave observations, yields a slope coefficient of 0.05, with a standard error of 0.003. Therefore, managers have an indication of whether their firms would survive or exit the market. However, the level of subjective probability is much lower than the actual survival rate. Even in cases where a manager answered there is no possibility of survival, more than 90% of them were still in business in February 2021.

Subsidy To evaluate the effect of public policies using managers' expectations, it is also important to assess the accuracy of their expectations about the policies. Because we study the effects of two grant subsidies, SPSB and EAS, on the survival of small businesses in the subsequent section, here we examine the accuracy of the manager's beliefs about the probability of receiving subsidies. Figure 3 (c) compares the subjective probability of receiving the SPSB by the next quarter and whether they actually received it. We make five bins for the subjective probability of receiving the subsidy and calculate the share of firms that received the subsidy in each bin. Regardless of the survey timing, on average, managers correctly predict whether they can receive the subsidy by the coming quarter. The regression of the granted dummy on subjective receiving probability controlling for survey wave-fixed effects, which includes 18,853 firm-wave-level observations, yields a slope coefficient of 0.53 with a standard error of 0.01. The managers are again pessimistic, but only slightly: the probability of receiving the subsidy is, on average, 20 percentage points higher than the subjective probability. Meanwhile, Figure 3 (d) compares for the EAS. On average, managers correctly predict the possibility of receiving this subsidy as well. The slope coefficient is 0.15, with a standard error of 0.01.

In summary, managers have relatively accurate expectations for sales growth but are overly pessimistic for survival regarding the business outcome. This makes sense because sales could be predicted on the basis of daily business outcomes. On the contrary, whether the survival of a firm depends on a wider variety of factors, such as the availability of bank loans and changes in public health regulation, and are affected by their long-term expectations on the business environment. It is also worth stressing that managers have relatively accurate expectations on the SPSB than the EAS. This could be because of the simplicity and transparency of the eligibility criteria of the SPSB.

4 Comparing Ex-ante and Ex-post Policy Evaluation

In this section, we demonstrate how managers' expectations on outcomes can be used to conduct ex-ante policy evaluation and compare the results with ex-post policy evaluation using realized outcomes. Specifically, we evaluate the effects of subsidy policies on business survival expectations and compare the effects using expectations to the results of policy evaluation using the realized survival outcome. We focus on SPSB and EAS, among others, because these are two of the largest transfer programs for saving firms and employment in the first year of the COVID-19 pandemic in Japan, disregarding emergency loan programs.[3]

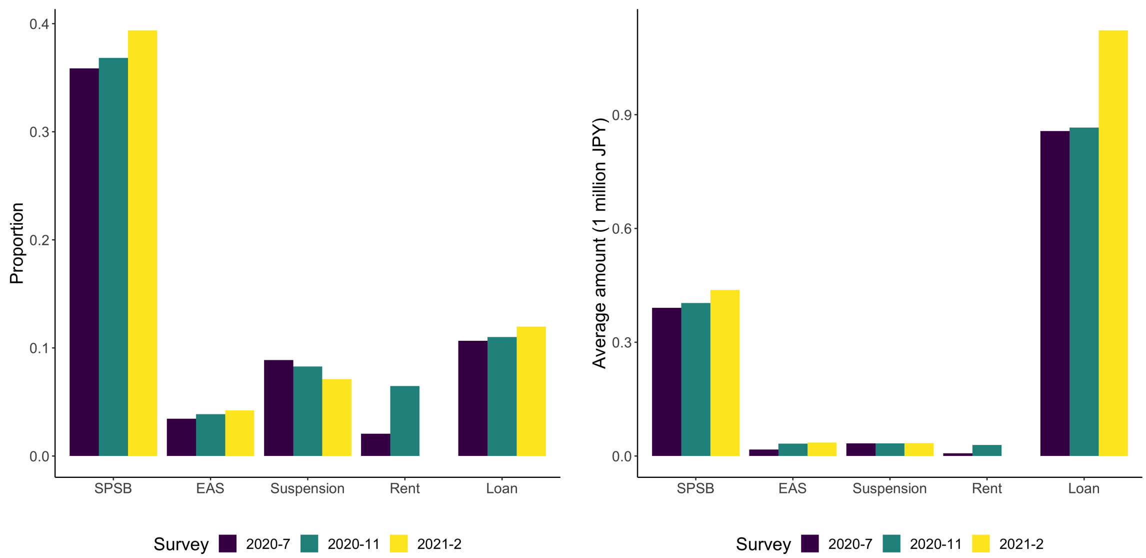
The SPSB and EAS have different policy goals: While the SPSB was newly introduced to help small firms continue their business operations to survive the COVID-19 pandemic, the EAS was started in the 1970s to protect employment by subsidizing leave allowances after the oil crisis and expanded in response to the pandemic. One could argue that the EAS was enough to serve both policy goals: saving small businesses with employment and protecting employment, whereas others could contend that it should have been accompanied with the SPSB because the EAS does not help small businesses without employment. Given the size and emergency of these subsidies during the pandemic, selection of an effective subsidy policy and evaluation of the potential impacts of the policy in an unprecedented situation were urgently needed.

In Kawaguchi et al. (2021), we used the May survey results and showed that the expectation for receiving the SPSB increased the subjective survival probability, whereas the expectation for receiving the EAS did not. This section addresses the issue whether this ex-ante policy evaluation is aligned with the evaluation of the subsidies using realized outcomes.

4.1 Subsidy Schemes

The government introduced various subsidy schemes during the pandemic, including the SPSB, the EAS, the Suspension Subsidy, the Rent Subsidy, and the Novel Coronavirus Disease Special Loan. In the survey, we asked the managers about expectations for receiving them and the actual amount they could receive. Figure 4 (a) shows the proportion of firms that received the subsidies. More than 30% of firms in the sample received the SPSB, whereas less than 10% received other subsidies. Figure 4 (b) shows the average amount of subsidies received by the firms. The Novel Coronavirus Disease Special Loan is the largest, while the SPSB is the largest, excluding loans.

[3]From February 2020 to August 2021, a total of about 5.5 trillion yen in the SPSB and about 4.2 trillion yen in the EAS have been provided.



(a) Proportion

(b) Average amount

Figure 4: Is subsidy used by small businesses?

Note: Panel (a) shows the proportion of firms received each subsidy and Panel (b) shows the average amount of each subsidy. The subsidy schemes include the Subsidy Program for Sustaining Businesses (SPSB), the Employment Adjustment Subsidy (EAS), the Suspension Subsidy, the Rent Subsidy, and the Novel Coronavirus Disease Special Loan. Purple, green, and yellow bars are made based on the July, November, and February surveys, respectively.

4.2 Impact Evaluation Using Regression Discontinuity Design

The eligibility criteria of the SPSB and the EAS set a cut-off in the sales growth rate. We use this discontinuity to estimate the effect on the expected and realized firm survival.

The SPSB provides grants of up to JPY 1 million ($\approx$ USD 10,000) to the self-employed and up to JPY 2 million ($\approx$ USD 20,000) to small businesses, with limitations on the amount of sales decline from the previous year. The eligibility criteria are as follows: (1) at least one month of year-on-year sales in 2020 declined by more than 50%; (2) the firm must have been in operation since before 2019; and (3) its capital is below JPY 1 billion, or it employs fewer than 2,000 employees in the case of corporations. The decline in sales must be proven based on the sales ledger, which is the basis for taxation on profits. The application process is simple: the eligible firm only needs to access the specific website and submit the form, the copy of its sales ledger, and its identity certificate. The subsidy is usually transferred directly to the company's bank account within two weeks of application. The subsidy scheme was announced on April 8, 2020, and applications opened on May 1, 2020.

The EAS reimbursed part of the payment of the leave allowance up to JPY 15,000 per day per employee. This compensation scheme was established in 1975 in response to exogenous and temporary recessions, such as oil shocks, under the premise that retaining the workforce was more efficient than reducing and reemploying workers for a temporary shock. Under normal economic conditions, to receive the grant, the firm should prove that it has maintained employment through leave, training, or workplace reassignment during the recession. To be eligible for the EAS, firms should prove that their year-on-year monthly sales had decreased by 10% or more for three consecutive months, in principle. In March 2020, the criterion of decline in sales was relaxed to a 10% decline in a single month, as for the COVID-19-related sales decline. On April 1, in response to the growing shock of COVID-19, the sales decline criterion was further relaxed to a 5% decline in a single month in 2020.

4.2.1 The Effects of Subsidy Program for Sustaining Businesses

To be eligible for the SPSB, sales in at least one month should decline more than 50% relative to the same month of the previous year. Therefore, we can consider a fuzzy RDD for identifying the local average treatment effect. We use the worst year-on-year monthly sales from January 2020 to each survey month as the running variable, with the cut-off point at the value of -50%. The treatment variable is the amount of the SPSB received by the survey month. To observe the effects of subsidies on firms' survival, we mainly consider the subjective survival probability and actual survival status at the end of the year as the

Table 3: Effect of receiving the Subsidy Program for Sustaining Businesses

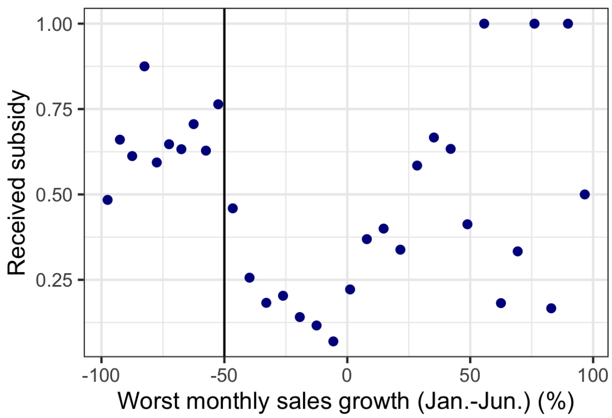
(a) Full sample

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.105*	(0.060)	527	1019
Nov	0.181**	(0.081)	498	1027
Survival dummy				
Jul	0.042**	(0.021)	457	900
Nov	0.051**	(0.023)	483	989
Employment (Count)				
Jul	-0.818	(1.073)	770	1434
Nov	0.772	(1.371)	320	726
Investment (Million JPY)				
Jul	-1.074	(0.803)	344	724
Nov	-0.633	(0.538)	534	1074

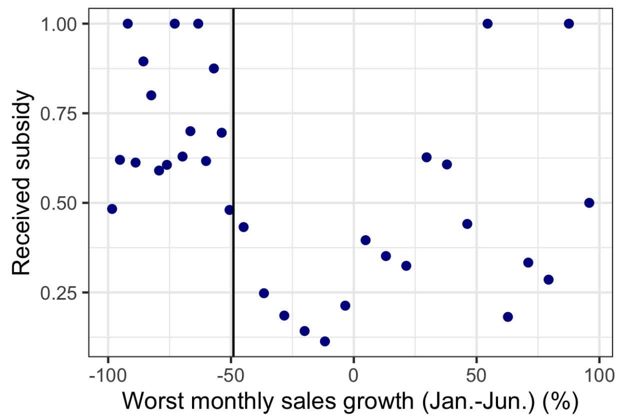
(b) Sample restricting to property owners

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.102*	(0.058)	177	410
Nov	0.221*	(0.119)	175	419
Survival dummy				
Jul	0.043*	(0.023)	253	555
Nov	0.035	(0.023)	381	793
Employment (Count)				
Jul	-1.091*	(0.630)	275	593
Nov	0.361	(1.635)	408	864
Investment (Million JPY)				
Jul	-0.233	(0.203)	274	589
Nov	-1.072	(0.905)	295	624

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. This table shows the estimation results based on the RDD using the cut-off points of eligibility criteria for the subsidies. Survival probability is the probability of continuing business until the end of 2020 (measured in % divided by 100). Survival dummy is an indicator of whether the firm survived at the end of 2020. Employment is the number of employees. Investment is the amount of investment by the firms (measured in million JPY). Panel (a) uses the full sample, whereas Panel (b) targets only property owners. Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).



(a) cutoff=-50



(b) cutoff=-49

Figure 5: Portion of firms receiving the SPSB

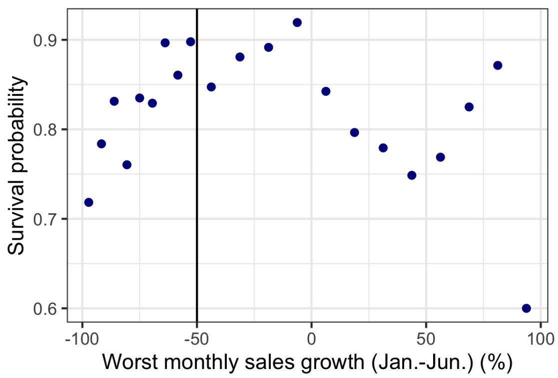
Note: These figures show the regression discontinuity plots for the proportion of firms receiving the SPSB by July 2020. Panels (a) and (b) show the results when we set -49 and -50 as cutoffs, respectively. The x-axis is the worst year-on-year monthly sales growth from January 2020 to the month before the survey month. We select the bin number based on the integrated MSE-optimal evenly spaced method.

outcome variables. Thus, the estimated effects can be interpreted as the percentage point increase in the subjective probability and actual survival status when the manager receives JPY 1 million.

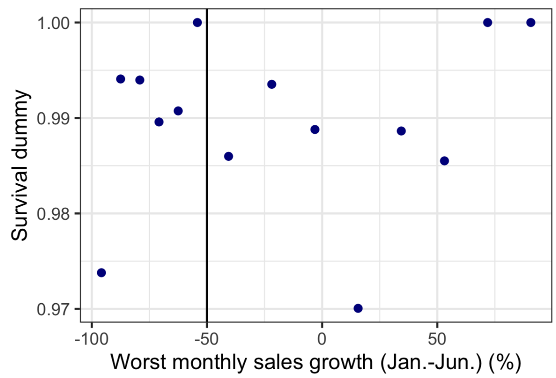
One problem in this analysis is that there is a mass point at the value of -50%, as shown in Figure A5. The distribution suggests that some managers whose worst sales growth was strictly above -50% likely moved to the value of -50%. There are two types of potential manipulations here. First, there are managers who manipulate their actual sales to -50% to receive the SPSB (manipulators). Second, there are managers whose sales growths were strictly above -50% but answered the rounded number of -50% (misreporters). Theoretically, we should exclude manipulators but keep the misreporters group as control.

We decide to keep the sample at the value of -50% and regard all as a control for the following reasons. First, including misreporters at the value of -50% as a control is appropriate. Second, including manipulators as a control will bias the treatment effect estimate just in the conservative direction, because they had a potential of achieving a higher sales growth and, nevertheless, became eligible for the SPSB. Third, there seems to be more misreporters than manipulators at the value of -50%, because the probability of actually receiving the SPSB increases when the sample at -50% is included in the control group (Panel a of Figure 5) but not when included in the treatment group (Panel b of Figure 5).

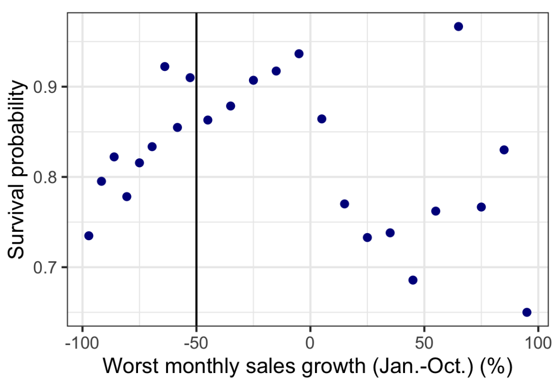
We discuss other validation tests after showing the main results.



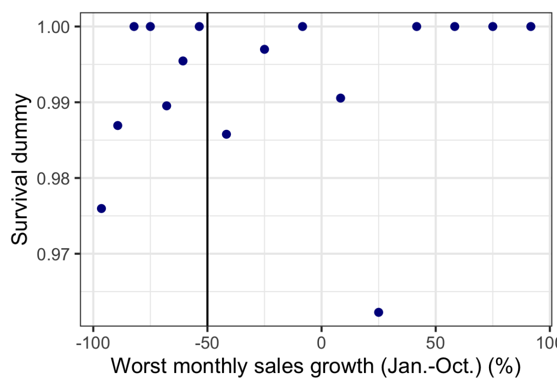
(a) Subjective Probability (July survey)



(b) Survival (July survey)



(c) Subjective Probability (November survey)



(d) Survival (November survey)

Figure 6: Subsidy Program for Sustaining Businesses

Note: These figures show the regression discontinuity plots for the effects of the SPSB on subjective probability of survival and actual survival status. In Panels (a) and (c), the y-axis is the subjective probability of continuing the business until the end of 2020, using the managers' answers in the July and November surveys, respectively. In Panels (b) and (d), the y-axis is the realized survival indicator until the end of 2020 collected from the February pre-survey. The x-axis is the worst year-on-year monthly sales growth from January 2020 to the month before the survey month. We select the bin number based on the integrated MSE-optimal evenly spaced method.

Panels (a) and (c) of Figure 6 show that the subjective probability of survival jumps at the eligibility cutoff in both July and November surveys. For visualization, we use equally-spaced bins for which the number of bins is chosen to minimize the integrated mean squared errors.

Panel (a) of Table 3 shows the estimation results. It uses the local linear model for the point estimation, where the bandwidth is chosen by minimizing the local mean squared errors estimated by the local quadratic model. The bias is corrected and the standard errors are robust according to Calonico et al. (2014). The results suggest that if the amount of subsidy received is JPY 1 million, a manager's prospect for survival until the end of 2020 improves by 10.5 and 18.1 percentage points in July and November 2020, respectively. These are large effects, given that the average subjective probability of continuing business until the end of 2020 is 84% in July and 87% in November.

In Kawaguchi et al. (2021), we conducted the similar analysis using the subjective probability of managers receiving the SPSB as a treatment variable instead of the received amount. We showed that the subjective survival probability increased by 19.8 percentage points if the manager was certain about receiving JPY 1 million of the SPSB. We replicate the same analysis using the answers in the July and November surveys in the top two rows of Table A7. The treatment variable is the probability of receiving the SPSB at the survey month. We set the probability 100% for the firms that had already received the SPSB by the survey month. The subjective survival probability increases by 19.7 and 29.5 percentage points in July and November if the manager is certain about receiving the SPSB. The numbers are comparable with the results in the May survey.

We also find that the SPSB had significant positive effects on actual survival; if the amount of subsidy received exceeded JPY 1 million, the actual survival rate improves by 4–5 percentage points, as shown in the third and fourth rows of Table 3. This uses the same local linear specification with the optimal bandwidth to minimize the local mean squared error. Panels (b) and (d) of Figure 6 show that the actual survival rate jumps at the eligibility cutoff in both the July and November surveys, using equally-spaced bins minimizing the integrated mean squared error for visualization.

Meanwhile, the subsidy did not affect the firm's quarterly investment and employment. Figure 6 shows that the effects of the SPSB on subjective survival probability and actual survival at the threshold. In Table A7, we also report the results when the outcome variable is the actual survival rate and the treatment variable is the subjective probability of receiving the SPSB. It shows that the actual survival rate increases by 4-6 percentage points if the manager is certain about receiving the SPSB.

One possible concern other than manipulation and misreport is a confounding by other

Table 4: Effect of receiving the Employment Adjustment Subsidy

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.507	(3.567)	290	627
Nov	0.405	(0.636)	407	1284
Survival dummy				
Jul	-0.021	(0.473)	293	605
Nov	-0.015	(0.095)	384	1196
Employment (Count)				
Jul	-4.967	(48.415)	291	627
Nov	-5.315	(16.359)	407	1284
Investment (Million JPY)				
Jul	15.303	(96.371)	309	642
Nov	-5.772	(28.136)	406	1283

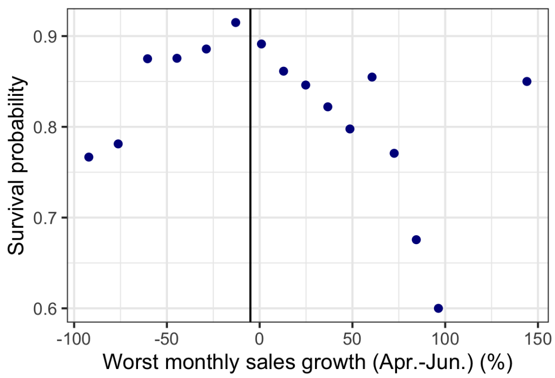
Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. This table shows the estimation results based on the RDD using the cut-off points of eligibility criteria for the subsidies. Survival probability is the probability of continuing business until the end of 2020 (measured in % divided by 100). Survival dummy is an indicator of whether the firm survived until the end of 2020. Employment is the number of employees. Investment is the amount of investment made by the firms (measured in million JPY). Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

policies. For instance, the government simultaneously implemented another type of subsidy scheme, such as the Rent Subsidy, with the same eligibility criteria. As a robustness check, we restrict the sample to the property owners, who need not get the Rent Subsidy and use the same exercise. Panel (b) of Table 3 confirms that the results do not change.

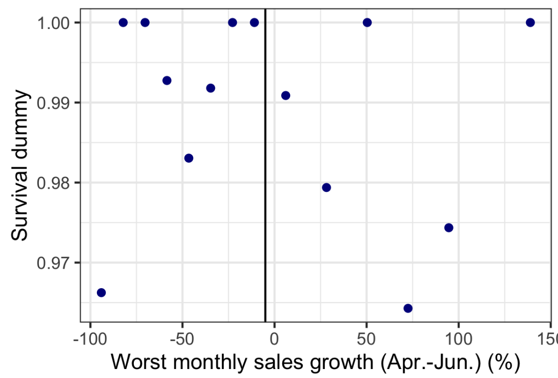
Another remaining concern is regarding the nature of the unbalanced survey. The business managers in the July and November RDD sample can be different from the sample who answered the actual survival question in the February pre-survey. To alleviate this concern, we replicate the analysis by restricting the sample to those who answered the actual survival question in the February pre-survey. Table A9 reports the results when the sample is restricted to them. The estimated effects of SBSP are similar to the previous analysis: 12.3 and 17.2 percentage points on the subjective survival probability in July and November and 4.2 and 5.1 percentage points on the actual survival rate. Thus, the results are qualitatively unchanged.

4.2.2 The Effect of Employment Adjustment Subsidy

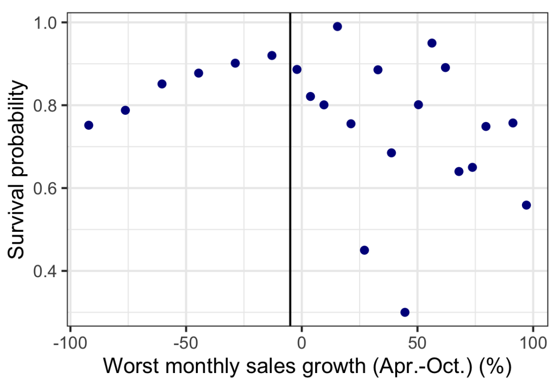
To be eligible for the EAS, firms had to prove that their year-on-year monthly sales had declined by over 5% after April 2020. We use the worst monthly year-on-year sales growth



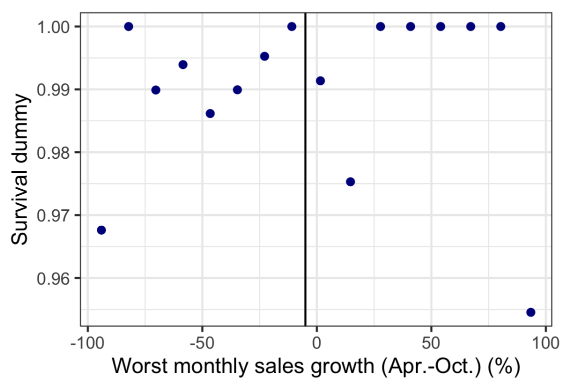
(a) Subjective Probability (July survey)



(b) Survival (July survey)



(c) Subjective Probability (November survey)



(d) Survival (November survey)

Figure 7: Employment Adjustment Subsidy

Note: These figures show the regression discontinuity plots for the effects of the subsidy on subjective probability of survival and actual survival status. In Panels (a) and (c), the y-axis is the subjective probability of continuing the business until the end of 2020, using the managers' answers in the July and November surveys, respectively. In Panels (b) and (d), the y-axis is the realized survival indicator until the end of 2020 collected from the February pre-survey. The x-axis is the worst year-on-year monthly sales growth from April 2020 to the month before the survey month. We select the bin number based on the integrated MSE-optimal evenly spaced method.

between April and the month before the survey month in 2020 as the running variable, with the cut-off point at the value of -5%. The treatment variable is the amount of the EAS received by the survey month. We found no discernible gap above or below the threshold. As shown in Table 4, we find no statistically significant effects on the firm's survival. Although the policy goal of this subsidy was to maintain employment, the effect on employment growth was not statistically significant, either. We do not find any statistically significant effect for the EAS by changing the treatment variable to the probability of receiving the EAS (Table A8). Figure 7 shows no effect of the EAS on subjective survival probability and actual survival. Table A10 shows the results when the sample is restricted to the respondents with the February pre-survey. No significant effects are found for the EAS.

4.3 Comparing ex-ante and ex-post policy evaluations

The analysis shows that the ex-ante policy evaluation using managers' expectations for survival could successfully find that the SPSB would increase the survival rate of small businesses. It also successfully predicted that the EAS might not serve this policy goal. The ex-ante policy evaluation of the SPSB, however, overpredicted the magnitude of the impact, probably because managers were overly pessimistic for survival. Therefore, the analysis should focus on the exaggeration bias when quantifying the potential impact using managers' expectations for survival.

On the contrary, the estimated effects of the SPSB are similar when replacing the received amount of subsidy with the probability of receiving the SPSB. This could be because the eligibility criterion for the SPSB was simple and transparent. As shown in Section 3, the managers had an almost rational expectation for the receipt of the SPSB. This is an additional benefit of using a simple formula for distributing the subsidy under crisis. The simple formula allows business managers to correctly anticipate the receipt of the subsidy and it helps policy makers to improve the accuracy of ex-ante policy evaluation using managers' expectations.

4.4 Validation tests

In the Appendix, we have multiple validation tests of the regression discontinuity analysis. In Panel (a) of Table A11, we check the continuity at the -50% cut-off point of predetermined variables, including employment, registered capital, and registered sales in 2019, by applying a sharp RDD to these variables. None of the predetermined variables shows a discontinuous change at the cut-off point. This provides suggestive evidence of the continuity of the potential outcome regression functions.

Panel (b) of Table A11 applies the same fuzzy RDD as the main analysis to placebo variables, including the manager's subjective probability of holding the Tokyo Olympics, infection containment, and mass vaccination. Crossing the cut-off point only decreases the subjective probability of holding the Tokyo Olympics in the July survey. This suggests that crossing the cut-off point could affect managers through a channel makes them more pessimistic about the Tokyo Olympics. No other coefficients are statistically significant. This implies that crossing the cut-off point is unlikely to affect the manager's belief in survival in other channels than the SPSB, such as psychological effects.

In Table A12, we perform the same analysis at the -5% cut-off for the same predetermined and placebo variables. None of the coefficients were statistically significant. Insignificance of the predetermined variables provides suggestive evidence of the continuity of the latent outcome functions. Insignificance of placebo variables indicates that crossing the cut-off is unlikely to affect managers' subjective beliefs other than the subjective survival probability.

In Tables A13 and A14, we apply the RDD to placebo cut-off values: -40% and -60% for the SPSB and 0% and -10% for the EAS. We find no significant effects at these placebo cut-off values. Table A15 examines the continuity of the running variable at -50% and -5% cutoffs. This indicates that the observed effects at -50% will not be an artifact of the rounded answers. The running variables are not statistically significant at -50% but statistically significant at -5%. Therefore, some manipulations may occur at -5%. However, regardless of the validity of the design, the EAS was unlikely to have an impact, because the take-up rate was substantially low.

5 Conclusion

In this study, we evaluated the accuracy of the expectations of small business managers from several aspects and used them to study the potential impacts of subsidy policies on the survival of small businesses during the COVID-19 pandemic. We showed that the managers' expectations on their business outcomes are strongly correlated with the realized outcomes even during a crisis. The managers' expectations about firm survival predicted the actual survival rates, but substantially underestimated. This possibly affected the performance of ex-ante policy evaluation using managers' expectation data. The effects of receiving the SPSB and EAS on a firm's expected survival probability and the realized survival rate were estimated to have the same sign. Thus, the ex-ante policy evaluation could obtain an effective policy using the expectation data. However, the estimated magnitude of the effect of receiving the SPSB on the expected survival probability was more than twice the estimated magnitude on the realized survival rate.

This study has several limitations. First, it only compares the ex-ante and ex-post policy evaluations of the two subsidy policies. Whether an ex-ante policy evaluation can predict the impact of other types of policies, such as the provision of interest-free loans, is worth investigating. Second, it only analyzed the expectations during the COVID-19 crisis and does not explicitly compare the performance of an ex-ante policy evaluation between normal times. The finding that managers underestimate their survival probability and overestimate the impact of a subsidy may be specific to a crisis. Third, the data only cover the first year of the COVID-19 crisis and does not study how the managers' expectations behave in other type of crisis. How small businesses react to this environmental change is an issue of future research.

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A Appendix

A.1 Selected Questions in the Questionnaire

Monthly realized sales growth

By what percentage did your monthly sales change compared to the sales in the same month of the last year? Please answer the approximate rate of change corresponding to the accounting book. For example, if there is no change compared to the same month of the last year, please write "0%". If it decreased by 10%, please write "-10%", and if it increased by 10%, please write "10%".

* If the company was established after the same month of the previous year, please write 9999.

Expectation about receiving subsidy

Approximately, what is the probability (in percentage terms) that your company will receive the SPSB, the EAS, the Suspension Subsidy, the Rent Subsidy, and the Novel Coronavirus Disease Special Loan in this quarter and next quarter? If you do not expect to receive any new subsidy during the period, please write 0%. If your company does not have a forecast, please respond based on the your best guess.

1. Probability of receiving the SPSB during this quarter and next quarter respectively.
2. Probability of receiving the EAS during this quarter and next quarter, respectively.
3. Probability of receiving the Suspension Subsidy during this quarter and next quarter, respectively.
4. Probability of receiving the Rent Subsidy during this quarter and next quarter, respectively.
5. Probability of receiving the Novel Coronavirus Disease Special Loan during this quarter and next quarter, respectively.

Amount of subsidy received

How much has your company received the SPSB, the EAS, the Suspension Subsidy, the Rent Subsidy, and the Novel Coronavirus Disease Special Loan by the end of the last month? Please answer the cumulative amount from January 2020. * Please round off to the nearest 10,000 yen.

1. Amount of the SPSB received by the end of last month
2. Amount of the EAS received by the end of last month
3. Amount of the Suspension Subsidy received by the end of last month
4. Amount of the Rent Subsidy received by the end of last month
5. Amount of the Novel Coronavirus Disease Special Loan received by the end of last month

Subjective probability of survival

Approximately, what is the probability (in percentage terms) you think that your company will be able to continue its business until the end of this year? If your company does not have a forecast, please respond based on your best guess.

Firm's survival

Q1. Has your company experienced any changes in business, relocation, or closure since May 2020? (Any number)

1. Changed the business content
2. Relocated a office
3. Closed
4. There was no change in business, relocation, nor closure of business

Q2. We would like to ask those who have closed their businesses after May 2020. When did you close your business?

A.2 Survey design

To construct the panel data, we conducted 4 surveys in May 2020, July 2020, November 2020, and February 2021. In the May survey, we sent the survey to 28,169 subjects who had registered as a top manager of a corporation, self-employed, or freelance (hereafter, these three are collectively referred to as "top manager") at the time of annual registration renewal of the survey company in summer 2019. The May survey consisted only of the main survey, while each of the July, November, and February surveys consisted of the pre-survey and the main survey.

The target of the July pre-survey was managers who did not respond the May survey and have less than 20 employees. The November pre-survey was sent to those who answered the May survey but did not answer in the July survey. The pre-survey in February 2021 was sent again to all 28,169 top managers. The pre-surveys asked about the current occupation of the respondent, whether the respondent closed business since May 2020, and the number of employees in the business if it is still open. In addition, the July and November pre-surveys asked for information that was missing from the previous survey due to a lack of responses, including sales figures. In the pre-survey in February 2021, if managers indicated that they withdraw their business after May 2020, we asked the timing of their exit.

The main survey in May was sent to all 28,169 top managers. The surveys in July and November were conducted to managers who responded either the previous surveys or the pre-surveys and who have 20 or fewer employees. The February survey was sent to the respondents of the pre-survey and who have 20 or fewer employees. The resulting numbers of survey respondents in the main survey were 12,364 in May 2020, 8,866 in July 2020, 7,732 in November 2020, and 9,227 in February 2021. Figure A1 graphically explains the targets of the pre-survey and survey, the respondents, and the subjects that passed the data cleaning for each wave.

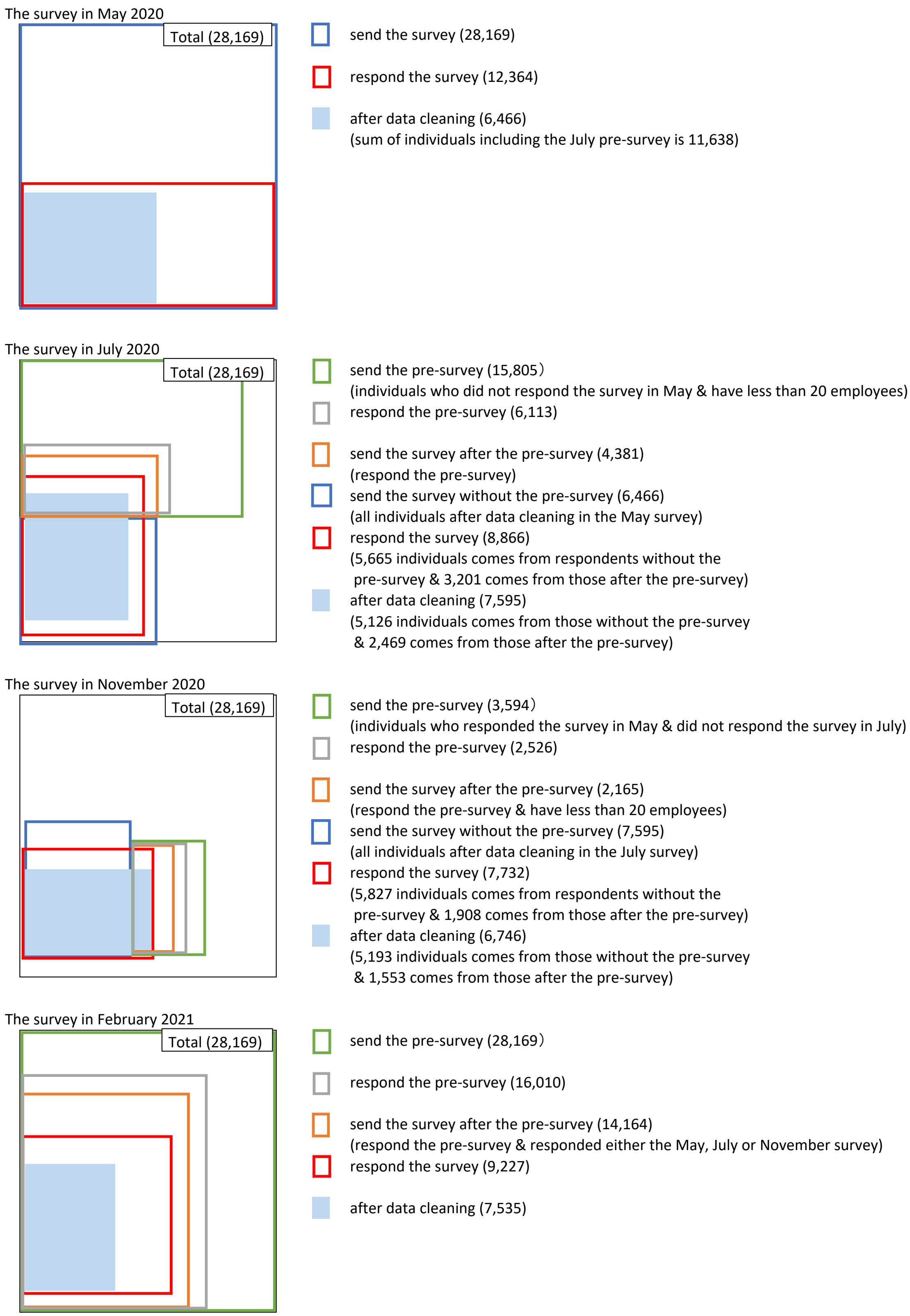

Figure A1: Sample size by each survey

A.3 Data cleaning

We detected and dropped inconsistent or unrealistic answers in the following three steps. First, we only kept respondents that answered the employment size in December 2019, which we asked in every survey.

Second, we dropped subjects whose response time was unreasonably short, that is, less than 10 percentile of response time among the respondents. Through this process, 1,089 subjects in the May survey, 866 subjects in the July survey, 753 subjects in the November survey, and 921 subjects in the February survey were dropped.

Third, we dropped subjects whose answers on the number of employees in the survey were substantially inconsistent with the information that they provided to the survey company when they registered as respondents, or inconsistent respondents with registered employment and employment as of December 2019. Specifically, we did not use subjects whose answers on employment size differed by at least 3 ranks among 13 ranks (less than 5, 5–9, 10–19, 20–29, 30–49, 50–99, 100–199, 200–299, 300–499, 500–999, 1,000–2,999, 3,000–4,999, and 5,000 or more) between the registered number and the number at the end of 2019, or between the end of 2019 and the time of the survey. Through this process, we dropped 827 subjects in the May survey, 193 subjects in the July survey, 39 subjects in the November survey, and 552 subjects in the February survey.

Fourth, we restricted the sample to respondents whose number of employees, including the manager, was no greater than 20. This is the definition of small business by the Japanese government. Among the remaining subjects, 521 respondents in the May survey, 37 in the July survey, 16 in the November survey, and 4,755 in the February survey have 20 or more employees. As a result, we used 11,638 subjects in the May survey, 7,595 subjects in the July survey, 6,746 subjects in the November survey, and 7,535 subjects in the February survey in our analysis.

A.4 Distribution of Forecast Error

Figure A2 shows the distribution of the forecast errors in sales growth, as defined in Table A1, for each survey. It shows that the forecast errors for the Q2 (April-June) sales as predicted in May are left skewed, with a mean of -9.43 percentage points and a skewness of -1.14, indicating that some managers were too optimistic in May. One explanation for this optimism may have been due to the fact that the emergency declaration in force then would drastically reduce the number of new cases and the infection would be brought under control. The distributions of forecast errors become symmetric with a mean of -0.39 and a skewness of -0.68 in November. The government introduced subsidies for promoting traveling and eating out during the fall, but the managers were not overly optimistic about the policy. However, in February, the distribution became more left-skewed again, with a mean of -1.46 and a skewness of -1.11, possibly because managers did not fully anticipate such a rapid increase of the alpha variant, even though the emergency declaration was re-declared in January.

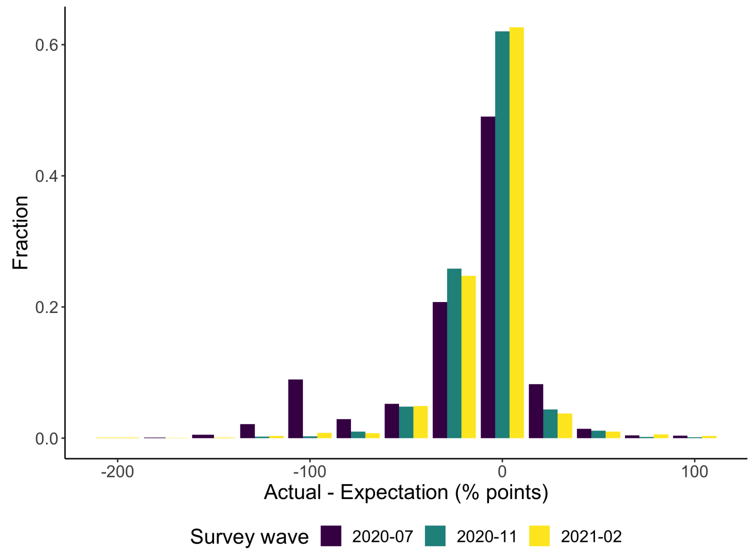

Figure A2: Accuracy of expectations for sales growth

Note: This figure shows the distribution of one-quarter-ahead forecast errors realized in each survey. The forecast errors are defined as gaps in the actual and expected sales growth. Purple, green, and yellow bars are related to sales growths in Q2, Q3, and Q4 2020, respectively. Purple shows the gap of realized Q2 sales growth and its expected value in May. Green shows the gap of realized Q3 sales growth and its expected value in July. Yellow shows the gap of realized Q4 sales growth and its expected value in November.

Table A1: Definitions of forecast errors by surveys

Survey Wave (t)	Forecast Error in Sales Growth $(t-1)$
July	Q2 2020 Realization − Q2 2020 Expectation in May
November	Q3 2020 Realization − Q3 2020 Expectation in Jul
February	Q4 2020 Realization − Q4 2020 Expectation in Nov

Table A2: Definitions of forecast updates by surveys

Survey Wave (t)	Update in Sales Growth Expectation ($t+1$)
July	Q4 2020 Expectation in Jul − Q4 2020 Expectation in May
November	Q1 2021 Expectation in Nov − Q1 2021 Expectation in Jul
February	Q2 2021 Expectation in Feb − Q2 2021 Expectation in Nov

A.5 How Are Managers' Expectations Updated?

When managers update their sales expectations, they should know their recent forecast errors. Then, do the managers learn from these mistakes? To evaluate managers' ability to adjust expectations, we examine the effect of a manager's forecast error on the last quarter's sales growth and the manager's forecast update on the next quarter's sales growth.

We define the forecast update in each survey as the change in forecasts from the last survey to the current survey regarding the sales growth in a future fixed quarter. For instance, the forecast update in the July survey represents the degree of the firms' change in forecast on Q4 (October–December) sales growth in the July survey from the May survey. At the time of this update, the firms should know the extent of their forecast errors on Q2 (April–June) sales growth. If managers realized they were too optimistic (or pessimistic) in the past quarter, they may want to update their sales growth forecast downward (or upward) in the next quarter. See the summary of the definitions in Table A2.

Figure A3 shows the distribution of expectation updates on sales growth for each survey. Managers updated their expectations downward, on average, by 13.4 percentage points in the July survey, probably because managers tended to overestimate Q2 sales growth in May and managers realized the recovery from the COVID-19 pandemic was harder than expected. In the November and February surveys, the updates were more modest: the average changes were -1.6 and 2.1.

Panel (a) of Table A3 shows the results of regressing forecast updates on the past forecast error. Columns (1)–(3) show the regression results of each survey, and column (4) shows the pooled result controlling for firm and survey wave-fixed effects. The results confirm the significant positive correlations between forecast updates and past forecast errors. This is consistent with the hypothesis that firms tend to update their forecasts by learning from the past forecast errors. The correlations are smaller for the later surveys, indicating that firms adapted to the business environment under the COVID-19 pandemic, and became less sensitive to past forecast error.

We next examine how much of these updates are explained by the updates of COVID-19-related forecasts. Specifically, we consider the following equation:

$$\begin{aligned}(\text{Sales growth update } (t+1))_{it}^{w} = &\beta_1(\text{Forecast error } (t-1))_{it}^{w} + \beta_2(\text{Zerocase update})_{it}^{w} \\ &+ \beta_3(\text{Vaccine by } t+1, \text{update})_{it}^{w} \\ &+ \beta_4(\text{Olympic update})_{it}^{w} + \epsilon_{it}^{w},\end{aligned} \tag{1}$$

where t (= Q3 2020, Q4 2020, Q1 2021) represents the quarters in the calendar year of

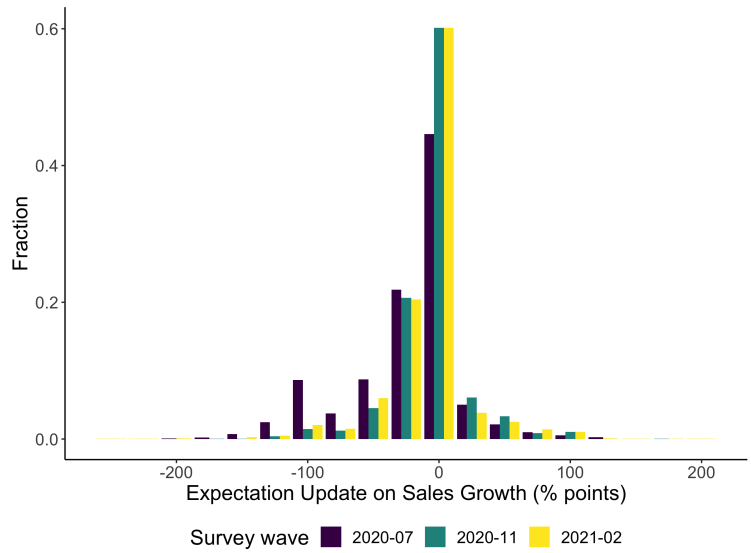

Figure A3: Distribution of sales growth forecast updates

Note: This figure shows the distribution of forecast updates on future sales growth. In each survey, the forecast update is defined as the change in forecasts from the last survey to the current survey. Purple, green, and yellow bars denote the July, November, and February survey, respectively. Purple shows the update of forecast about 2020 Q4 sales growth from May to July. Green shows the update of forecast about 2021 Q1 sales growth from July to November. Yellow shows the update of forecast about 2021 Q2 sales growth from November to February.

2020–2021, and w means survey waves (= July, November, February). The subscript t and superscript w are always one-to-one; July corresponds to Q3, 2020, November corresponds to Q4, 2020, and February corresponds to Q1, 2021. "(Sales growth update $(t+1))^w_{it}$" is the forecast update on sales growth for $t+1$ in w from $w-1$. "(Forecast error $(t-1))^w_{it}$" is the forecast error on sales growth for $t-1$. See the summary definitions in Table A1 and A2.

As the sales growth forecast is supposed to be updated considering the pandemic conditions, we include firms' updates on COVID-19-related forecasts. "(Zerocase update$)^w_{it}$" is the forecast update on the timing of infection containment from $w-1$ to w. If the expected timing of infection containment answered in survey w becomes earlier than that answered in survey $w-1$, this variable takes a negative value. "(Vaccine by $t+1$, update$)^w_{it}$"is defined as follows: (Vaccine by $t+1$, update$)^w_{it}$ = (D vaccine $[t+1|t])^w$ − (D vaccine $[t|t-1])^{w-1}$, where (D vaccine $[t+1|t])^w$ takes a value of 1 if the expected timing of mass use of vaccination at the time of survey w (= at time t) is in quarter $t+1$. Similarly, (D vaccine $[t|t-1])^{w-1}$ takes a value of 1 if the expected timing of mass use of vaccination at survey $w-1$ (= at time $t-1$) is in quarter t. Thus, "(Vaccine by $t+1$, update$)^w_{it}$" takes a value of 1 if the firm updates its expected timing of mass vaccination to be earlier and takes a value of -1 if the firm revises its expected timing as later. If firms do not change their stance on vaccine forecast, this variable takes 0. "(Olympic update$)^w_{it}$" is the forecast update on the subjective probability of hosting the Tokyo Olympics from survey $w-1$ to w.

In Panel (b) of Table A3, we control for the expectation updates of COVID-19-related events. The coefficients of past forecast errors are almost unchanged compared to Panel (a), and forecast updates on COVID-19-related events are mostly insignificant and have a small explanatory power. These results suggest that firms update their forecast on sales growth mostly based on their past forecast errors on their sales growth, or generally, forecast errors on factors specific to the own business performance rather than the aggregate environment.

The question remains whether this managers' response to the recent forecast error is reasonable or over-extrapolation. If managers over-extrapolate the recent shock to the future, their expectations are unstable. We examine this by following the approaches by Coibion and Gorodnichenko (2015) and Altig et al. (2020). According to their approach, we regress the forecast error about Q4 sales growth made from the manager's expectation in the July survey on the difference between the firm's expectations in the May and July surveys:

$$\begin{aligned} &\mathrm{RealizedQ4Sales}_i - \mathrm{ExpectedQ4SalesJuly}_i \\ &= \beta(\mathrm{ExpectedQ4SalesMay}_i - \mathrm{ExpectedQ4SalesJuly}_i) + \epsilon_i. \end{aligned} \tag{2}$$

If the update is correct, the coefficient is zero. If the update is an over-extrapolation, the coefficient is positive. For example, suppose that a firm's expected zero sales growth in May and updated to 1.0 in July, while the realized sales growth was 0.7. Then, the left-hand value is -0.3 and the right-hand value is -1.0, resulting in a coefficient of 0.3. The regression, which includes 1,248 firm-level observations, yields a slope coefficient of 0.21 with a standard error of 0.02 and an R-squared value of 0.09. This result is consistent with a coefficient of 0.34 in Altig et al. (2020). This analysis shows that when managers update their expectations, they mildly over-extrapolate the recent news.

Table A3: Updates and past forecast errors

(a) Correlation

	(1)	(2)	(3)	(4)
Dep.Var	20Q4	21Q1	21Q2	20Q4-21Q2
Forecast error (t-1)	0.708***	0.547***	0.465***	0.714***
	(0.021)	(0.034)	(0.021)	(0.036)
Num.Obs.	1411	1699	3694	6804
Firm FE	NO	NO	NO	YES
Survey FE	NO	NO	NO	YES
Survey wave	Jul 2020	Nov 2020	Feb 2021	All

(b) Correlation under controlling for other forecast updates

	(1)	(2)	(3)	(4)
Dep.Var	20Q4	21Q1	21Q2	20Q4-21Q2
Forecast error (t-1)	0.708***	0.544***	0.463***	0.712***
	(0.021)	(0.034)	(0.021)	(0.036)
Zerocase update	0.001	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Vaccine by t+1, update	-2.205	1.867	-1.268	0.339
	(2.585)	(1.929)	(1.093)	(1.683)
Olympic update	0.080**	-0.011	0.011	-0.017
	(0.032)	(0.021)	(0.017)	(0.021)
Num.Obs.	1409	1694	3676	6779
Firm FE	NO	NO	NO	YES
Survey FE	NO	NO	NO	YES
Survey wave	Jul 2020	Nov 2020	Feb 2021	All

Note: Columns (1)–(3) show the results of the regression equation (1) with (Panel b) and without (Panel a) control variables for the July, November, and February surveys, respectively. For column (1), the dependent variable is the managers' forecast update on sales growth in Q4 2020. "Forecast error $(t{-}1)$" in column (1) is the forecast error on sales growth in Q2 2020. For column (2), the dependent variable is the managers' forecast update on sales growth in Q1 2021. "Forecast error $(t{-}1)$" in column (2) is the forecast error on sales growth in Q3 2020. For column (3), the dependent variable is the managers' forecast update on sales growth in Q2 2021. "Forecast error $(t{-}1)$" in column (3) is the forecast error on sales growth in Q4 2020. Panel (b) additionally controls for expectation updates related to the COVID-19-related events. Column (4) shows the result of pooled regressions with firm- and survey-fixed effects. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A.6 Additional Figures and Tables

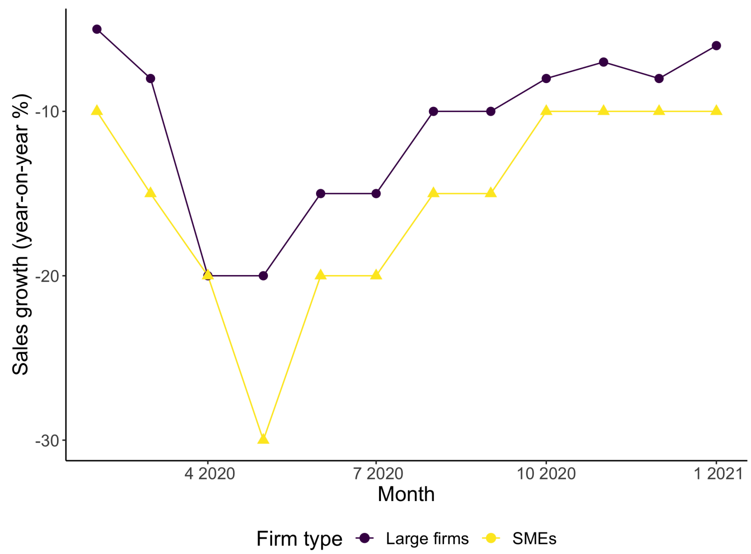

Figure A4: Realized year-on-year sales growth based on TSR data

Note: These figures are made by authors based on the survey data conducted by *Tokyo Shoko Research* (TSR). TSR defines firms whose capital is over 100 million JPY as large firms and others as SMEs. Purple line shows the year-on-year sales growth for large firms and yellow line shows that for SMEs.

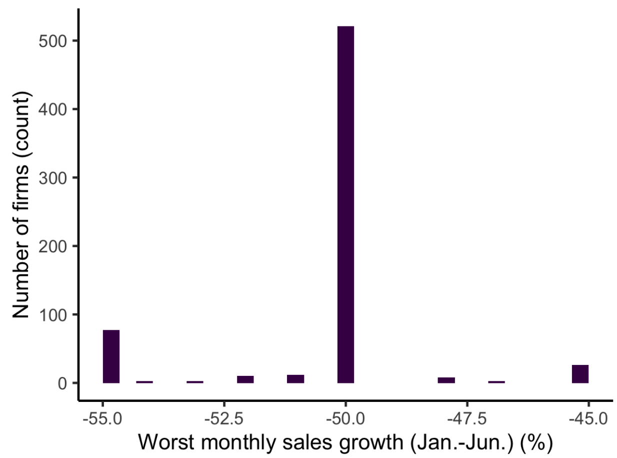

Figure A5: Distribution of the worst monthly sales growth

Note: This figure shows the number of firms by the worst monthly sales growth between January and June, 2020.

Table A4: Balance test for attrition based on regression

	Respondent dummy	Num.Obs.	Mean Dep.
Male	0.010	6917	0.849
	(0.014)		
Age	0.002***	6917	0.849
	(0.000)		
Ln(Capital)	0.002	6917	0.849
	(0.004)		
Ln(Sales)	-0.001	6917	0.849
	(0.005)		
|Forecast error|	0.000	2204	0.859
	(0.000)		
Prob. receiving SPSB	0.006	7545	0.828
	(0.009)		
Prob. receiving EAS	-0.033	7543	0.828
	(0.020)		
Prob. survival	0.081***	7595	0.828
	(0.017)		

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. The sample is respondents in the July survey. Table tests the balance of the respondents' attributes between the respondents in the February pre-survey and the non-respondents. The attributes include sex, age, sales at 2019, and registered capital. We examine the difference in their forecast errors at July, measured as absolute values of "Q2 2020 sales growth realization − Q2 2020 sales growth expectation in May." In addition, we examine the difference in their responses on the subjective probability of receiving the SPSB (EAS) by the end of 2020, the subjective probability of hosting Olympic and the subjective probability of survival by the end of 2020, measured in the July survey. Standard errors are in parentheses.

Table A5: Balance test for attrition

(a) Attribute and response

sample	Non-respondents			respondents			
	N	Mean	SD	N	Mean	SD	Test
Male	1044	0.887	0.317	5873	0.895	0.307	F= 0.542
Age	1044	54.809	10.049	5873	55.98	9.625	F= 12.939***
Ln(Capital)	1044	-5.747	1.102	5873	-5.724	1.156	F= 0.358
Ln(Sales)	1044	-3.375	0.787	5873	-3.383	0.811	F= 0.075
|Forecast error|	310	27.583	34.502	1894	24.744	31.432	F= 2.112
Prob. receiving SPSB	1299	0.436	0.477	6246	0.446	0.479	F= 0.402
Prob. receiving EAS	1298	0.069	0.231	6245	0.058	0.215	F= 2.689
Prob. survival	1309	0.796	0.291	6286	0.834	0.25	F= 23.36***

(b) Prefecture and sector

sample	Non-respondents		Respondents		
	N	Percent	N	Percent	Test
Prefecture	1044		5873		X2= 3.767
... Aichi	78	7.5%	365	6.2%	
... Hyogo	52	5%	276	4.7%	
... Kanagawa	62	5.9%	384	6.5%	
... Osaka	98	9.4%	528	9%	
... Others	590	56.5%	3326	56.6%	
... Tokyo	164	15.7%	994	16.9%	
Sector	1044		5873		X2= 2.993
... BtoB	225	21.6%	1339	22.8%	
... BtoC (less shock)	340	32.6%	1886	32.1%	
... BtoC (more shock)	195	18.7%	984	16.8%	
... Non-service	284	27.2%	1664	28.3%	

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. The sample is respondents in the July survey. Table (a) tests the mean differences of respondents' attributes between the respondents in the February pre-survey and the non-respondents. We present respondents' attributes including sex, age, sales at 2019, and registered capital. The difference of |Forecast error|, measured as absolute values of "Q2 2020 sales growth realization − Q2 2020 sales growth expectation in May," is also shown. In addition, we present response (the subjective probability of receiving the SPSB (EAS) by the end of 2020, the subjective probability of hosting Olympic and the subjective probability of survival by the end of 2020) in the July survey. Table (b) tests the differences of the share of respondents with a given attribute (prefecture and sector).

Table A6: Distribution of industry and size in the survey and the Economic Census

(a) the survey

No. of employees	1	2	3	4	5-9	10-19	Total
Industry							
Non-service	0.08	0.04	0.02	0.01	0.02	0.01	0.18
Service	0.39	0.20	0.07	0.04	0.07	0.04	0.82
Total	0.47	0.24	0.09	0.06	0.10	0.05	1.00

(b) the Economic Census

No. of employees	1	2	3	4	5-9	10-19	Total
Industry							
Non-service	0.03	0.04	0.03	0.02	0.05	0.03	0.19
Service	0.19	0.17	0.10	0.07	0.17	0.10	0.81
Total	0.22	0.21	0.13	0.09	0.22	0.13	1.00

Notes: The upper table presents the distribution of industry and firm size of the survey in May 2020, and the lower one shows the distribution in the Economic Census (2016).

Table A7: Effect of the probability of receiving the SPSB

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.197**	(0.082)	344	724
Nov	0.295***	(0.098)	312	722
Survival dummy				
Jul	0.060***	(0.023)	454	892
Nov	0.042**	(0.019)	300	694
Employment (Count)				
Jul	-0.418	(1.196)	525	1017
Nov	0.655	(1.836)	318	725
Investment (Million JPY)				
Jul	-1.143**	(0.486)	325	691
Nov	-0.695	(0.621)	530	1073

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. The treatment variable is the probability of receiving the SPSB at the survey month. We set the probability 100% for the firms that had already received the SPSB by the survey month. Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

Table A8: Effect of the probability of receiving the EAS

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.679	(2.126)	309	642
Nov	-0.682	(1.023)	408	1284
Survival dummy				
Jul	-0.015	(0.237)	293	606
Nov	0.046	(0.173)	385	1197
Employment (Count)				
Jul	-181.986	(1292.864)	451	687
Nov	18.043	(26.480)	407	1284
Investment (Million JPY)				
Jul	26.086	(65.009)	309	643
Nov	21.995	(42.355)	408	1284

Note: The treatment variable is the probability of receiving the EAS at the survey month. We set the probability 100% for the firms that had already received the EAS by the survey month. Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

Table A9: Effect of receiving the SPSB: February pre-survey respondents

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.123*	(0.072)	456	899
Nov	0.172*	(0.088)	481	988
Survival dummy				
Jul	0.042*	(0.021)	457	900
Nov	0.051**	(0.022)	483	989

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. This table shows the estimation results based on the RDD using the cut-off points of eligibility criteria for the subsidies. The analysis targets only the respondents of the February pre-survey. Survival probability is the probability of continuing business until the end of 2020 (measured in % divided by 100). Survival dummy is an indicator of whether the firm survived at the end of 2020. Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

Table A10: Effect of the probability of receiving the EAS: February pre-survey respondents

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.829	(6.925)	278	590
Nov	0.326	(4.949)	384	1196
Survival dummy				
Jul	-0.021	(0.473)	293	605
Nov	-0.015	(0.095)	384	1196

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. This table shows the estimation results based on the RDD using the cut-off points of eligibility criteria for the subsidies. The analysis targets only the respondents of the February pre-survey. Survival probability is the probability of continuing business until the end of 2020 (measured in % divided by 100). Survival dummy is an indicator of whether the firm survived at the end of 2020. Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

Table A11: Effect of receiving the SPSB on covariates

(a) Predetermined variables

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Predetermined vars.				
Employment at 2019				
Jul	0.405	(0.632)	275	559
Nov	0.165	(0.763)	245	549
Log of registered capital				
Jul	-0.090	(0.222)	275	559
Nov	-0.257	(0.250)	258	574
Log of registered sales				
Jul	0.144	(0.164)	266	536
Nov	-0.070	(0.196)	260	575

(b) Placebo variables

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Placebo vars.				
Probability of Tokyo Olympic				
Jul	-0.136*	(0.070)	347	724
Nov	-0.180	(0.120)	294	652
Timing of infection containment				
Jul	-0.971	(1.251)	530	1022
Nov	-0.331	(1.670)	480	952
Timing of mass vaccination				
Jul	0.631	(1.046)	528	1019
Nov	0.387	(1.487)	305	677

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Predetermined variables are the employment, capital, and sales at the end of 2019. Placebo variables are subjective probability of holding Tokyo Olympic (% divided by 100), expected timing of infection containment and mass vaccination in Japan. We measure the expected timing for infection containment and mass vaccination as year-unit since the beginning of 2020, for example, 2.5 means June 2022. We see the continuity of predetermined variables by employing the sharp RDD at the cutoff point -50%, whereas we confirm that placebo variables are not confounding the main results by employing the fuzzy RDD. The treatment variable is the amount of the SPSB received by the survey month. Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

Table A12: Effect of receiving the EAS on covariates

(a) Predetermined variables

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Predetermined vars.				
Employment at 2019				
Jul	-0.094	(0.576)	532	717
Nov	0.030	(0.585)	497	1005
Log of registered capital				
Jul	-0.292	(0.222)	439	670
Nov	-0.060	(0.204)	498	1005
Log of registered sales				
Jul	0.209	(0.167)	438	670
Nov	0.671**	(0.286)	175	938

(b) Placebo variables

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Placebo vars.				
Probability of Tokyo Olympic				
Jul	-0.074	(4.658)	374	774
Nov	-0.212	(1.007)	350	665
Timing of infection containment				
Jul	3.602	(39.722)	347	754
Nov	1.336	(8.793)	350	665
Timing of mass vaccination				
Jul	2.434	(28.873)	351	751
Nov	1.268	(4.171)	350	661

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Predetermined variables are the employment, capital, and sales at the end of 2019. Placebo variables are subjective probability of holding Tokyo Olympic (% divided by 100), expected timing of infection containment and mass vaccination in Japan. We measure the expected timing for infection containment and mass vaccination as year-unit since the beginning of 2020, for example, 2.5 means June 2022. We see the continuity of predetermined variables by employing the sharp RDD at the cutoff point -5%, whereas we confirm that placebo variables are not confounding the main results by employing the fuzzy RDD. The treatment variable is the amount of the EAS received by the survey month. Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

Table A13: The effects of the SPSB at placebo cutoffs

(a) Cutoff = -40

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.023	(3.420)	589	572
Nov	-0.001	(0.238)	581	567
Survival dummy				
Jul	0.226	(0.281)	455	465
Nov	0.024	(0.034)	564	545
Employment (Count)				
Jul	-17.329	(84.808)	589	572
Nov	-31.947	(53.280)	815	973
Investment (Million JPY)				
Jul	5.816	(7.208)	823	878
Nov	4.500	(8.029)	807	911

(b) Cutoff = -60

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	1.780	(2.083)	24	313
Nov	0.265	(0.379)	199	777
Survival dummy				
Jul	1.212	(5.385)	176	684
Nov	0.036	(0.032)	192	748
Employment (Count)				
Jul	6.875	(13.560)	24	313
Nov	-0.761	(2.317)	199	777
Investment (Million JPY)				
Jul	-35.550	(111.429)	17	298
Nov	-0.943	(0.658)	199	777

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. This table shows the results of placebo tests under different cutoff points of eligibility criteria for the subsidies. We set -40 as the cutoff point in Panel (a) and -60 in Panel (b). Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

Table A14: The effects of the EAS at placebo cutoffs

(a) Cutoff = 0

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	11.026	(11.775)	192	597
Nov	-1.166	(0.930)	456	1268
Survival dummy				
Jul	4.070	(8.352)	474	652
Nov	-0.164	(0.139)	457	1181
Employment (Count)				
Jul	10.326	(55.969)	355	644
Nov	1263.646	(3899.404)	257	1241
Investment (Million JPY)				
Jul	-97.901*	(57.177)	606	728
Nov	-3404.954	(9971.693)	258	1241

(b) Cutoff = -10

	Subsidy (Million JPY)	S.E.	N (Left)	N (Right)
Survival probability 2020				
Jul	0.666	(0.553)	445	792
Nov	0.463	(0.317)	466	1453
Survival dummy				
Jul	0.086	(0.174)	429	755
Nov	0.310	(0.210)	439	1358
Employment (Count)				
Jul	-13.468	(18.974)	445	792
Nov	2.847	(18.141)	466	1453
Investment (Million JPY)				
Jul	20.625	(12.862)	359	748
Nov	-4.525	(9.462)	466	1453

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. This table shows the results of placebo tests under different cutoff points of eligibility criteria for the subsidies. We set 0 as the cutoff point in Panel (a) and -10 in Panel (b). Standard errors are in parentheses. We employ a mean square error optimal bandwidth and a local-linear regression. The bias is corrected and the standard errors are robust according to Calonico et al. (2014).

Table A15: Continuity test of the worst sales growth at the cutoffs

	p.values
SPSB	
Jul	0.116
Nov	0.446
EAS	
Jul	0.000
Nov	0.000

Note: This table shows the result of the continuity test for the density of the running variable at -50% and -5% cutoffs. We implements manipulation test using the local polynomial density estimators proposed in Cattaneo et al. (2020).