Zombies, Again? The COVID-19 Business Support Programs in Japan[1]

Takeo Hoshi (University of Tokyo)
Daiji Kawaguchi (University of Tokyo)
Kenichi Ueda (University of Tokyo)

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ABSTRACT

We designed and conducted a firm-level survey on the use of COVID-19-related government programs, in collaboration with Tokyo Shoko Research, LTD (TSR). Combining the survey results with the financial statements of the respondent firms, we investigated the factors behind the allocation of various government programs. We find that firms that had low credit scores before the COVID-19 pandemic were more likely to apply for and receive the subsidies and concessional loans offered by the Japanese government in 2020. Firms with low credit scores are not necessarily zombies, which are defined to be the firms that are non-viable but kept alive by assistance from creditors and/or government. Our result suggests that the government assistance may have also subsidized some poorly performing firms that were not yet zombies before the pandemic.

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1. Introduction

The COVID-19 pandemic was not only a health shock but also an economic shock of unprecedented magnitude. The shock was largely unexpected and forced many governments to put together emergency responses, which included pandemic containment measures and economic policies. An important economic policy was the provision of various supports for businesses. In many countries, business firms received subsidies, public guarantees on their loans, loans with subsidized rates and/or lenient conditions, tax breaks and other assistances so that they could tide over the COVID-19 shock without laying off many workers. For example, the central government of Japan allocated at least 3 percent of GDP for concessional loan programs to ease the liquidity problems of firms, and the amount of COVID-19-related loans made by financial institutions in 2020 was about 10 percent of GDP.

Those policy measures mainly aimed at preventing the failure of viable firms and the loss of productive employment relations. If the COVID-19 shock were just a temporary macroeconomic shock, the short-lived policies to support existing businesses would make sense as everything would go back to normal and the temporary disruption of economic restructuring would not be very costly. If the shock turns out to be persistent, however, the liquidity problem for many firms turn into a solvency problem. The government would then face an unattractive tradeoff: continuing the support programs would create the zombie problem that stifles long-run growth, but phasing out the support abruptly would risk the cliff-edge of business failures. The problem becomes even more serious if the shock is not only a macroeconomic shock but also a reallocation shock that requires economic restructuring beyond mere financial reorganization, as suggested by Barrero et al. (2020), Bloom et al. (2020), and Davis et al. (2020). Supporting the incumbent firms with no longer profitable businesses would lead to the zombie problem. Not only do unproductive firms remain, but also productive firms are discouraged to grow due to congestion caused by zombie firms in product, capital, and/or labor markets. The concessional loan programs would become especially problematic because the added loans create debt overhang that slows down necessary restructuring and new investment.

Policymakers and journalists alike warned that the current massive business support program in developed countries might cause "zombification" of post COVID-19 economies.[2] To see if those warnings are valid, we need to know how the business support programs were directed and which firms took up the programs. In particular, it is important to know whether those support programs have been used mainly for the firms that were already struggling before the pandemic.

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[2] Media coverage on "zombification" includes "Germany's bail-out brings worries about its long-term effects," *The Economist*, September 19, 2020, "Will Japan see a new generation of zombie firms?," *The Economist*, September 26, 2020, "What to do about zombie firms," *The Economist*, September 26, 2020, "European Zombification becomes even scarier," *Financial Times*, December 3, 2020, "Zombies Could Stunt the Bank Recovery," *The Wall Street Journal*, January 12, 2021, and "Zombie Companies Feed Off the Living," *The Japan Times*, December 8, 2020.

To understand these issues, Tokyo Shoko Research, LTD. (TSR), a major Japanese credit rating agency, and the Center for Research and Education on Policy Evaluation (CREPE) at the University of Tokyo, jointly designed and conducted a firm-level survey on the impacts of COVID-19 shocks, as well as on the applications and receipts of various business support programs. Specifically, we looked at three grants and subsidy programs for businesses,[3] two tax special treatments,[4] COVID-19 related concessional loans programs by two government banks,[5] private sector banks, and other (normal) lending by government banks and private sector banks.

We combine the survey results with the corporate financial data provided by TSR. Our sample includes not only large listed firms but also small unlisted businesses. Based on the original survey, we examine how the funds from various COVID-19-related measures were allocated across firms. In other words, for each type of program, we study the characteristics of the firms that are more likely to receive the support from the government. The government support was designed to help SMEs that suffered large declines in sales during the pandemic but some design flaws that were not known in advance may have led to selection of firms that were already non-viable before the pandemic.

We pay special attention to the pre-COVID-19 credit worthiness of the firms that receive these public supports. A challenge in our empirical analysis is the fact that the negative shock due to the pandemic may be correlated with the credit worthiness of the firm before COVID-19. Correlation between the shock and credit worthiness before COVID-19 may entail a spurious correlation between the pre-COVID-19 credit worthiness and the likelihood to apply for the support programs. To avoid this potential problem, we control for the year-on-year sales growth in every month, firm size, and industry- and prefecture-fixed effects.

Across the various support programs, including subsidies, grants, and concessional loans, we consistently find that a firm with a lower credit score before the pandemic was more likely to receive the support, conditional on the magnitude of the COVID-19 shock during the pandemic (approximated by the year-on-year sales growth), the firm size, the industry, and the prefecture where the firm is located. We check the robustness of all results by changing the functional form of the regression model, the measurement of the financial health, and the selection of the (sub-)sample.

In particular, we find that the subsidies and grants flow more to the firms that were judged to have a low credit score before the pandemic. For example, a firm having a credit score one standard deviation below the mean was 7.7% more likely to receive the business continuation grant. We also

[3] They are the Business Continuity Grant, the Office Rent Grant, and the special terms for Employment adjustment subsidy.
[4] Essentially, one is the corporate tax moratorium and the other is the property tax reduction.
[5] The two government banks are Japan Finance Corporation (JFC) and Shoko Chukin Bank.

find that firms with low credit scores before the pandemic were more likely to receive the concessional loans. For example, a firm with credit score one standard deviation below the average was 28.1% more likely to receive a concessional loan from the Japan Finance Corporation (JFC).

Moreover, the negative correlation between the pre-pandemic credit score and the receipt of loans or the loan amount are substantially stronger for concessional loans from private sector banks, which come with government guarantees, than for standard loans from those banks. For example, our analysis reveals that a firm with one standard deviation lower credit score borrowed about 0.42 log points more concessional loans from private sector banks, but about 0.12 log points more standard loans from those banks. The result is consistent with the hypothesis that the government guarantee makes banks' lending standards more lenient because the banks would not suffer from potential defaults. A back of the envelope calculation shows that about 20% of the total borrowing amount of the concessional loans were taken up by those that TSR labeled as "the firms that creditors should exercise caution with."

Our key finding is that the non-negligible fraction of the support measures ended up helping the firms that were already distressed before the outbreak of the COVID-19 pandemic. This finding suggests that the current policy to combat the seemingly temporary pandemic shock may sustain non-viable firms and make potentially profitable firms face debt overhang even after the pandemic is contained. Thus, policymakers need to carefully design the process of unwinding the support measures to avoid the risk of making the temporary shock into a permanent brake on the economy and creating the zombie problem again in Japan. The process of unwinding has to deal with restructuring or exits of firms that were already unviable before the crisis.

The rest of the paper is organized as follows. Section 2 reviews the literature in economics related to our inquiry. Section 3 reviews various public support programs for businesses introduced in Japan during the COVID-19 crisis. Section 4 describes the data that we use for the analysis. Section 5 reports the main results on the characteristics of the firms that receive various supports from the government. Section 6 examines the robustness of the results using alternative measurement of firm solvency and the analysis sample. Section 7 concludes by pointing out some directions for future research.

2. Related Literature

The paper adds to the literature on potential "zombification" of post-COVID-19 economies, which is growing in both academic research and journalistic discussion. The zombie firms are the firms that are in permanent distress but stay in business without going through serious restructuring, thanks to assistance provided by their creditors and/or governments. The concept of zombie firms was originally developed to understand the economic stagnation in Japan in the late 1990s. The Japanese banks were found to extend credit more often to seemingly non-viable corporations, as Peek and Rosengren (2005) found. The obvious cost of zombie firms is that productive resources (capital and/or human resources) are put into less productive uses. As Caballero et al. (2008) showed, congestion created by zombie firms reduces the profitability of non-zombies and potential entrants, thus, it harms the process of creative destruction and economic growth.

The zombie problem in Japan is likely to be a factor that explains the "negative exit effect" puzzle. The exit effect in the productivity decomposition à la Foster et al. (2001) refers to the improvement of the aggregate productivity resulting from exits of firms that had productivities lower than the industry average. For Japan, the researchers consistently find such an exit effect to be negative overall, implying that many exiting firms have productivities *higher* than the industry average or equivalently the firms with very low productivities often continue to stay in the market. The papers that find the negative exit effects include Fukao, Kim, and Kwon (2006), which use establishment-level data and Nishimura, Nakajima, and Kiyota (2005), which use firm-level data.

In the mid-2000s, as large Japanese banks were finally forced to get rid of non-performing loans, many large zombie firms appeared to have disappeared or been restructured, as Fukuda and Nakamura (2011) argued. However, the zombie problem may still haunt the Japanese economy. Ueda and Dovchinsuren (2020) report that the disparity of marginal product capital across firms has been increasing steadily. The problem is especially serious for small and medium-size enterprises (SMEs). Ikeuchi et al. (2018) find a negative exit effect using extensive data on SMEs. Recent research by Miyakawa (2021) finds that a large part of the negative exit effect may be explained by the acquisition of relatively well performing SMEs by large companies, but even after controlling for such effect, he still finds the remaining exit effect to be negative.

After the global financial crisis and the sovereign debt crisis that followed in Europe, the zombie problem attracted attention in many European countries. The IMF (2013) examined the pros and cons of various credit support policies adopted by many advanced countries. McGowan et al. (2018) studied firm-level data from several OECD countries and found that the proportion of zombie firms rose in many countries after the global financial crisis. Moreover, they found that zombie congestion tends to reduce the productivity growth, especially for young firms. Acharya et al. (2020) examine panel data for over a million firms from 12 European countries and find that zombie firms depress not only productivity growth but also many other variables related to corporate performance, including markups and product prices, and may generate deflation.

More generally, the paper relates to the growing literature on the policies toward the businesses hurt by the COVID-19 crisis. Gourinchas et al. (2020) estimate a large increase in the failure rate of small and medium-size enterprises (SMEs) if no government support is provided. They also show that it is possible to support the vulnerable firms selectively to avoid a sudden increase in the failure rate without much fiscal cost. Brunnermeier and Krishnamurthy (2020) examine how the support policy should take into account somewhat different types of problems faced by different firms. For example, they point out that liquidity provision is desirable for many SMEs facing severe liquidity constraints while making restructuring through bankruptcy process easier is better for large firms with solvency problems. The Group of Thirty (2020) points out that the main problem has already shifted from liquidity to solvency and argues:

> "The problem is worse than it appears on the surface, as massive liquidity support, and the confusion caused by the unprecedented nature of this crisis, are masking the full extent of the problem, with a "cliff edge" of insolvencies coming in many sectors and jurisdictions as support programs lose funding and existing net worth is eaten up by losses."
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> *Group of Thirty, 2020, pp.1*

There are a few studies on the impacts of business support programs in various countries. Granja et al. (2020) study the allocation and impacts of the Paycheck Protection Program (PPP) for SMEs in the US, which provided loans to troubled SMEs through private sector lenders approved by the US Small Business Administration (SBA). They find that the loans were not well targeted and flowed to regions not relatively affected that much. They also find that many SMEs used loan proceeds to pay for expenses other than payrolls and/or saved it. The impact on employment, the stated goal of the program, was found to be very small. Chetty et al. (2020) also examined the employment impact of the PPP and make a similar finding. They used the eligibility cutoff at 500 employees for the PPP and found it took $377,000 to save a job.

In contrast to these papers, Doniger and Kay (2021) find that the PPP saved a large number of jobs, mostly at very small firms well below the eligibility threshold of 500 employees. They argue the employment impact would have been even bigger if the PPP loans had been targeted for smallest firms. Balyuk, Prabhala, and Puri (2021) also find that small firms were less likely, perhaps reluctant, to get PPP loans in early stage of the program, although this tendency was not much observed for the firms with prior lending relationships with small banks. Bartlett and Morse (2020) found that the PPP improved their (subjective) prospect for survival of more than six months for very small businesses, but the hope may have disappeared quickly if they did not have good relationships with small banks. Joaquim and Netto (2021) point out another problem of the PPP coming mainly from the different objectives of the government (employment protection) and the banks (loan relationship and profits).

Core and De Marco (2020) examine the expansion of the government loan guarantee program in Italy. They find that the guaranteed loans were made more quickly by large banks with better information technology (IT) systems to the firms with existing lending relations. Hancké et al. (2020) look at programs in Germany and the UK aimed at helping businesses and find that the results of the apparently similar programs were very different. The UK policy was not effective in preventing layoffs while, apparently, the same policy protected employment in Germany. Boddin, D'Acunto, and Weber (2020) examine how the loans guaranteed by government programs in Germany and the firms with zombie features are more likely to take up the programs. Jappelli, Pelizzon, and Plazzi (2021) argue that the firm-level effects of any government support for non-financial firms in EU countries should depend on fiscal space of each country and find supportive evidences on such corporate-sovereign nexus during the pandemic.

For programs in Japan, Morikawa (2021) examined the relationship between productivity of firms before the pandemic and the receipt of government relief programs based on an original survey. He found that firms that received the government supports were more likely to exhibit low productivity (measured by labor productivity and TFP) before the COVID-19 crisis. His survey, however, did not take into account more detailed information such as credit score, the type of banks, and the lending amount. Uesugi et al. (2021) used the survey enumerated by Research Institute of Economy, Trade and Industry to describe how the COVID-19 affected Japanese firms and how the firms responded to the shock. The survey reveals that 47% of the respondent firms used the concessional loan program offered through the private banks, 42% of them used the business continuity grant, and 37% of them used the employment adjustment subsidy. These figures show that a large fraction of firms took up the publicly offered business support programs to respond to the COVID-19 shock. Similar to our findings, Uesugi et al. (2021) also report that the firms with low credit scores were more likely to take up these programs, except for the employment adjustment subsidy. They, however, do not examine the correlation between the credit score and the program take up conditional on the size of COVID-19 shock that each firm experienced. Thus, they cannot exclude the possibility that the firms with low credit scores got the business supports because they suffered larger shocks. For public loan guarantee programs before the pandemic, Ono and Yasuda (2017) found a similar moral hazard problem.

3. Support Programs in Japan During the COVID-19 Crisis

The Japanese government has introduced numerous policies to help firms combat their financial difficulties due to the COVID-19 pandemic. They can be classified into four major categories: grants and subsidies, special tax treatments, concessional loans, and administrative guidance and free consultations. Some of those programs introduced a new set of special terms for the existing program. For example, the employment adjustment subsidy increases the replacement rate of the wage subsidy, which explicitly aims at maintaining employment by supporting firms. We focus on several key programs in our regression analysis below. This section provides a brief overview of all public support programs designed to help corporations to survive the pandemic.

3.1. Grants and Subsidies

At least 15 grants and subsidies were introduced in 2020. These can be grouped into three types. First, there are some grants (*kyufukin*) aimed at providing immediate help for SMEs experiencing acute sales losses. These grants include the Business Continuity Grant (*jizokuka kyufukin*) and the Office Rent Grant (*yachin shien kyufukin*) and are administered by the central government (the Small and Medium Enterprise Agency). In 2020, the central government allocated funds for those grants in two sets of supplementary budget bills, one passed by the Parliament in April and the other in June.[6] In total, about 4 trillion yen was allocated to the Business Continuity Grant and about 2 trillion yen to the Office Rent Grant. The sum is about 1 percent of GDP, which is about 540 trillion yen in 2020.[7]

The Business Continuity Grant is a one-time grant of 2 million yen for a SME or 1 million yen for a sole proprietor. The eligibility criteria are (a) the recipient's monthly sales dropped more than 50% compared to the same month in the last year; and (b) the recipient established their business during or before 2019 and are willing to continue their business.

The Office Rent Grant is a one-time grant to partially reimburse rents up to 1 million yen per month for six months for a SME or up to 0.5 million yen per month for six months for a sole proprietor. The eligibility criteria are (a) the recipient's monthly sales dropped more than 50% compared to the same month in the last year; or (b) the recipient's three-month sales dropped more than 30% compared to the same three months in the last year.

Second, several subsidies (*hojokin*) are designed to incentivize SMEs to make forward-looking fixed investments, such as installing digital equipment to allow remote working, renovating office and shop spaces to ensure social distance, and so forth. These are provided mainly through two government sponsored institutions, the Organization for Small and Medium Enterprises and Regional Innovation and the Japan External Trade Organization. Major ones are subsidies under the Programs

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[6] Note that because our survey was conducted in late 2020, sample firms are not affected by another supplementary budget bill that passed Parliament in January 2021 in the same 2020 fiscal year (i.e., April 2020 to March 2021).
[7] Budget numbers follows Unami (2021), supplemented by the webpage information of the Ministry of Finance (https://www.mof.go.jp/budget/budger_workflow/budget/fy2020/fy2020.html#3hosei), the Ministry of Economics, Trade, and Industry (https://www.meti.go.jp/main/yosan/yosan_fy2020/index.html), and Japan Finance Corporation (https://www.jfc.go.jp/n/finance/search/covid_19_m.html).

to Promote Productivity Revolution (*seisansei kakumei suisin jigyo*).[8] These subsidies existed before the pandemic but were expanded to help firms adjust their businesses to respond to the pandemic.

Third, several subsidies (*joseikin*) are enhanced to maintain employment as much as possible. A major one is the Employment Adjustment Subsidy, which existed before the pandemic but was expanded substantially during the pandemic. The Ministry of Labour, Health, and Welfare directly administers this subsidy. The central government allocated about 0.5 trillion yen for this subsidy in total in two supplementary budgets.

It covers a firm's cost of paying furloughed workers or providing off-the-job training (Off-JT). If the firm is a SME and not laying off any workers, the subsidy pays 100% of the furlough payment or the wages for the workers who received the Off-JT (3/4 if it is a large firm). If the SME is laying off some workers, the subsidy pays 4/5 of the furlough cost or wages for workers in the Off-JT(2/3 if a large firm). These special terms are more generous than pre-COVID-19 ones, which covered 2/3 of the furlough cost or the wages for workers in the Off-JT (1/2 for large firms), regardless of the layoffs.

The maximum allowance per day, per worker was also increased from 8,370 yen to 15,000 yen. For a case of Off-JT, an additional 2,400 yen per worker, per day is granted to the SME (1,800 yen for large firms). Before the pandemic, the excess allowance for Off-JT was 1,200 yen regardless of the size of the firm. The period of eligibility for a firm to receive the employment adjustment subsidy was also relaxed to 100 days per year and 150 days per three years. The sales loss criteria for the eligibility was changed from 10% average sales drop over three months relative to the same three months last year to 5% monthly sales drop relative to the same month last year.

Other employment related subsidies (*joseikin*) include a direct payment to furloughed workers in case their employers do not pay, and grants to firms if they allow workers to take additional paid leave to take care of their children during school closures.

In the statistical analysis below, we focus on two grants (the Business Continuity Grant and the Office Rent Grant) and one subsidy (the Employment Adjustment Subsidy), since these are the major grants and subsidies aimed at helping firms that suffered from the COVID-19 pandemic.

3.2. Special Tax Treatments

[8] One of those subsidies is called the Business Continuity Subsidy (*jozokuka hojokin*), which sounds similar to Business Continuity Grant but is totally different.

In March 2020, the government announced the one-year grace period for any tax payments (e.g., corporate income tax, consumption tax, etc.) for firms that experienced drops in their monthly operating incomes by more than 20% compared to the same month last year (Corporate Tax Moratorium).[9] The one-year grace period also applies to sole proprietors who experience financial difficulties caused by the pandemic.

A tax refund, by carrying back this year's loss from the previous year's corporate income tax, are generously allowed. It had always been generous for firms with capital that do not exceed 100 million yen, but it is now allowed for all firms with capital of less than 1 billion yen. Moreover, corporations are allowed to deduct a wide range of COVID-19-related expenses and losses, including purchases of surgical masks and disinfectants and losses from unused raw foods at affected restaurants.

Property tax reduction on buildings, machineries, and equipment were also introduced in March 2020. The property tax on buildings, machineries, and equipment that a firm already owns was reduced to zero percent, if the firm's three-month sales dropped by more than 50% compared to the same months last year. The tax is reduced to a half if the sales drop was less than 50% but more than 30%. Even before the pandemic, lower property tax rates, which differ among prefectures, applied for newly purchased machinery and equipment for three years. In March 2020, the reduced property tax rates were extended to newly purchased business-related buildings.

3.3. Concessional Loans

Regarding special concessional loans related to COVID-19, at least 25 programs were introduced by the end of 2020. These can be grouped into two types: programs for loans originated by government financial institutions and those for loans originated by private sector banks. The major government financial institutions that provide the special concessional loans are the Japan Finance Corporation (JFC) and the Shoko Chukin Bank.[10] The government financial institutions provide preferential loans for SMEs even in the normal periods, but the special concessional loans are more generous than the usual preferential loans.

The key COVID-19-related special loan programs by these two government financial institutions share common terms and conditions. In March 2020, loan rates for the first three years were lowered by 0.9% to 0.21% for SMEs and to 0.46% for other firms. This is widely applied to firms

[9] This program lasted only one year. The application period to this program was ended as of February 1, 2021, except for some special circumstances (e.g., the owner-manager is hospitalized).

[10] While the Japan Finance Corporation is wholly owned by the central government, about half of the Shoko Chukin Bank is owned by the central government. The rest of the Shoko Chukin Bank is owned by Small Business Associations and their member SMEs. Other government financial institutions that provide the special concessional loans include the Okinawa Development Finance Corporation, which is owned wholly by the central government and targets firms in the Okinawa prefecture.

that experienced sales drops of more than 5% compared to the normal sales.[11] More damaged firms effectively pay a zero rate as they can receive the interest subsidies with the same amount as the interest payments from the Organization for Small & Medium Enterprises and Regional Innovation. For this, the eligibility is restricted to those who experienced a sales drop of more than 15% for micro enterprises and 20% for SMEs. No collaterals are required for these loans, so these loans are called "effective zero interest loans without collaterals."

As for the concessional loans through the private sector banks, the main program is a reinforced system of public guarantees for bank loans for SMEs. In Japan, SME bank loan guarantees of 80% of the loan values by the governmental agencies have been widely used. For several years following the Global Financial Crisis, the government enhanced public guarantees to 100% for bank loans. This special scheme had just started to be phased out before the COVID-19 crisis hit. In March 2020, the government reintroduced the special scheme, guaranteeing 100% of SME loan values. The eligible firms are essentially those who faced more than a 15% monthly sales drop compared to the same month of the last year. Also, additional budgets are allocated for 80% guarantee programs for those firms with more than 5% sales drops.

The guarantee fees, which are usually around 1%, are cut to a half for SME firms with more than 5% sales drop or zero for SME firms with more than 15% sales drop and for microenterprises with more than 5% sales drop. The bank loan guarantees are provided by the Credit Guarantee Associations, sponsored by prefectural governments (and a few city governments) in each jurisdiction but insured by the Japan Finance Corporation (and, hence, eventually by taxpayers). Terms and conditions vary slightly across prefectures.

After May 1, the government expanded the program of "effective zero interest loans without collaterals" to private sector banks. In many prefectures, the interest subsidies are paid directly to private sector banks from the Organization for Small & Medium Enterprises and Regional Innovation. The maximum interest rate that banks can charge varies across prefectures but is set at around 1.5%. Note that the interest spread is positive as the ordinary deposit rates of any banks and short-term interbank rates have long been effectively zero in Japan. To use this program, the firms need to use the 100% guarantees with zero fee program specified above, hence, they need to meet the same eligibility criteria. Firms eligible for 100% guarantees with 50% fee program receive the half of the interests they pay. The program design is essentially the same as the program provided by the government financial institutions.

[11] Normal sales refers to the same month sales in any of the past three years. In the case of firms established between three and 13 months ago, the normal sales refers to either (a) the average sales in the previous three months; (b) the December sales in 2019; or the average sales from October to December, 2019 (https://www.jfc.go.jp/n/finance/search/covid_19_m.html).

Overall, the central government allocated about 15 trillion yen, or about 3 percent of GDP, for concessional loan programs to ease the liquidity problems of firms in total in two supplementary budgets. These budget numbers include the interest payments and loan guarantee fees, but do not include the loan principals advanced by government financial institutions. The amount of COVID-19-related loans made by those financial institutions is estimated to be at least 50 trillion yen, or about 10 percent of GDP.

3.4. Administrative Guidance and Free Consultations

Consultations regarding corporate management, including financial management, digitalization, and human resource management, are provided free by government agencies or government sponsored enterprises. Some of the subsidies, especially those that come with debt forgiveness, require the recipients to go through such consultations.

Several sets of administrative guidance were issued to large firms and government agencies requiring them not to discriminate against and rather to give favorable treatments to SMEs and sole proprietors. Also, the government agency keeps a closed eye on these issues by occasionally surveying SMEs and proprietors. Similarly, regarding labor standards, the government agencies closely monitor firm compliance.

4. Data

The primary dataset used in this study is the firm-level credit report compiled by Tokyo Shoko Research (TSR), which is a major credit rating agency in Japan and is the Japanese counterpart of Dun and Bradstreet's worldwide network. The data set is widely used by researchers on Japanese firms, for example, Bernard et al. (2019) and Carvalho et al. (2020). We are not aware of a systematic study that establish how representative the TSR data set is, but the data set aims to cover all firms in Japan regardless of their size, industry, and region. It includes information on the year of establishment, the head quarter location, the industry defined by the major product or service, the amount of sales, the number of employees, profit, and information regarding the CEO.

To this data set, we add the results of the original firm survey on the effects of the COVID-19 pandemic that the Center for Research and Education in Program Evaluation (CREPE) at the University of Tokyo designed and conducted jointly with TSR. TSR and CREPE invited the TSR email magazine subscribers to participate in the survey between October 26th and November 6th, 2020 (the questionnaire is shown in Appendix A). Among the 5,695 firms who responded to the survey, 4,093 firms are matched to the observations in the data set. Matching the information as of December 2019 is crucial so as to learn the firms' financial conditions before the pandemic.

To better understand the characteristics of the firms that responded to the special survey, we compare the characteristics based on the firms' information as of December 2019, extracted from the TSR database. We find that firms with higher credit scores, higher profits per employee, more employees, and that are not SMEs are more likely to have responded to the survey, as reported in Table B1 and Figure B1 of Appendix B. In terms of industry, the manufacturing and wholesale and retail sectors are overrepresented, whereas construction, real estate and lease, hotel and restaurant, and health and welfare sectors are underrepresented. We have to keep in mind that there are some potential biases introduced by the sample selection. Our sample has somewhat more larger firms with better performance compared with the entire database. Moreover, the industries that are considered to have suffered especially during the pandemic, such as hotel and restaurant, are underrepresented in our sample.[12]

The survey asks for the growth rate of sales of each month between February and September in 2020, relative to the same month in 2019. We interpret the answer to this question as the demand shock that the firm experienced during the pandemic. The survey also asks whether they applied for any of the various government grants, subsidies, and loan programs. For each program that a firm applied for, the survey asks the month when the application was filed, whether and when it was approved, and the amount received if the application was successful.

As we discussed in the last section, many support programs have an eligibility criteria in terms of the (maximum) sales decline that a firm experienced during the pandemic. Thus, we expect both the applications and the acceptances to depend on sales growth. All of these variables are available in the survey data.

The main inquiry of this study is whether the applications for, and the acceptances into, the support programs are correlated with the pre-pandemic performances of the firms. The key variable to measure the pre-pandemic performance is the credit score assigned to each firm by TSR as of December 2019. The credit score for a firm at a specific time is recorded as an integer between 0 and 100. The credit score is the sum of the sub-scores for four aspects of the firm performance: management quality (0-20 pts), growth judged by sales growth, profit growth, and the product market

[12] If we know how the firms are selected into the sample, we can correct the selection bias by estimating the model with weighted least squares with the weight for each observation determined by the likelihood of being selected into the sample. For example, Haltiwanger et al. (2017) and Dinlersoz et al. (2019) propose such estimation strategy. The important assumption here is that we know a fairly accurate sample selection model. Although we are not confident that we have a good model of sample selection in this case, we tried weighted least squares (WLS) estimation using our data. Specifically, we estimated a probit model for the selection using the credit score, ln(employment), and ln(sales in 2019) to calculate the propensity score. Then, we use the inverse of it as the weight for each observation to estimate the regression models for application to the support programs. The results are qualitatively similar to the ones that we report in the paper, although the point estimates (but not the signs) of some important parameters change and some become statistically insignificant.

prospect (0-25 pts), stability judged by the balance sheet strength and relationship with lenders, suppliers and client firms (0-45 pts), and transparency and reputation (0-10 pts).[13] The TSR credit scores are known to be positively correlated well with the actual defaults (Miyakawa, Miyauchi, and Perez, 2017 and Miyakawa and Shintani, 2020).

TSR expects the subscribers to their services to utilize the credit score to determine the creditworthiness of corporate customers, especially when they provide trade credits. TSR classifies the firms into five groups according to the credit score and gives a verbal label to each group. The firms with a score less than or equal to 29 are "*keikai* (caution)," those with a score between 30 and 49 are "*ichio keikai* (somewhat caution)," those between 50 and 64 are "*tasho chui* (attention)," those between 65 and 79 "*bunan* (safe)" and those between 80 and 100 are considered to be "*keikai fuyo* (no risk)." In the statistical analyses below, we divide the original value for the TSR credit score by 100, so that the range of the variable becomes [0, 1]. As an alternative measure of pre-pandemic performance, we use the profit per worker, per month. We should note that about 10% of firms do not report the profit, thus, the sample size is reduced when we use this alternative measure of performance.

Table 1 shows descriptive statistics for the sample. The average value of the credit score is 0.543 with standard deviation 0.067. The 1st percentile of the distribution is 0.40 and the 99th percentile is 0.70. The average profit per worker, per month is 109 thousand yen, which is roughly 1 thousand US dollars. The average total sales per worker, per month is 4,410 thousand yen, which is roughly equivalent to 40 thousand US dollars. The average number of employees is 160, whereas the standard deviation is about 3,000, suggesting there are many small firms and a small number of large firms in the sample. The 5th percentile of the employment is 3 and the 95th percentile is 435.

Turning to the year-on-year sales growth during the period between February and September of 2020, the average sales growth was -0.002 in February, hitting bottom at -0.141 in May and recovering to -0.076 in September. The time series pattern for sales growth resembles the mirror image of the time series development for the number of confirmed new cases of COVID-19 infection. The state of emergency covering all the regions of Japan was in force between April 16th and May 14th. The trough of the sales growth in May probably reflects the plummet in peoples' mobility during the state of emergency.

Since the eligibility criteria for several government support and loan programs include conditions on the minimum sales growth during the past months, we calculate the minimum for the year-on-year sales growth from February to September and use this for statistical analysis in the next section. The average for minimum sales growth is -0.305 with a standard deviation of 0.302. This

[13] An explanation of the credit score is found at: http://www.tsr-net.co.jp/guide/knowledge/glossary/ha_05.html (in Japanese only).

implies that the respondents' experiences are widely heterogeneous. The survey also asks for the sales prospect for 2021 relative to 2019. The average for this answer is -0.078, which is very much similar to the average sales growth in September 2020. Thus, the average firm seems to expect the economic condition in the fall of 2020 to continue into 2021 with no improvement.

The survey asks several questions about firms' applications to the government support programs, as well as loans by government financial institutions for SMEs (Japan Financial Corporation and Shoko Chukin Bank) and private sector bank loans with the governments' subsidy on interest and the 100% public guarantee. For each program applied for, a respondent firm is asked to provide the month of application, the month of approval (if approved), and the amount received (or will receive).

Table 1 shows that about a quarter of firms applied for the special terms of the Employment Adjustment Subsidy, as well as the Business Continuation Grant, whereas about 10% applied for the Office Rent Grant. Only about 4% applied for the Corporate Tax Moratorium and only about 1% applied for the Property Tax Reduction. The low numbers for the tax moratorium application may be due to the tax deadline being two months after each firm's accounting year-end, which may come after our survey. About 16% of respondent firms applied for the special loans from Japan Financial Corporation (JFC). About 6% applied for the special loans offered by Shoko Chukin and about 25% applied for the special loans from private sector banks. The receipt rate of the program is close to the application rates for most of the programs.

The bottom part of Table 1 reports the descriptive statistics for the amounts received from the government support programs and the amounts borrowed from the financial institutions. The average amount received as the Employment Adjustment Subsidy is about 8 million yen, whereas the average of the Business Continuation Grant is 4 million yen, and the average of the Office Rent Subsidy is 3 million yen. The average amount of the special loan is 60 million from JFC, 90 million from Shoko Chukin, and 50 million from private banks. The amount of a standard loan is 70 million from JFC, 80 million from Shoko Chukin, and 130 million from private banks. The amounts of concessional loans are much larger than the amounts of subsidies or grants. The amounts of the special loans are comparable to the amounts of the standard loans in the case of JFC and Shoko Chukin, but the average amount of special loans is about half of the average amount of standard loans in the case of private financial institutions.

To get an idea about how the likelihood of applying for or receiving a government support is correlated with the credit score for 2019, we look at the diagrams exhibited in Figures 1, 2, and 3. To create a diagram, we first divide the range of the 2019 credit score into equal size intervals (bins), and then calculate the proportion of the number of firms that applied for (or received) the government support for each bin. The bin size is set so that there are 20 intervals with equal length. Finally, we plot the application proportion (y-axis) against credit-score bins (x-axis), and add a linear regression line. The results for the government grants (the Employment Adjustment Subsidy, the Business Continuation Grant, and the Office Rent Grant) are reported in Figure 1 and the results for the concessional loans (by Japan Financial Corporation, Shoko Chukin Bank, and private sector banks) are reported in Figure 2. In each figure, the upper panel shows the application rate and the lower panel shows the approval (receipt) rate. Figure 3 compares the actual loan amounts by lenders and loan types, concessional or standard loans. For this figure, the upper panel reports the results for concessional loans and the lower panel reports the results for standard loans.

Looking at Figure 1, both the application rate and the approval rate for all three government grants and subsidies are negatively correlated with the credit score of 2019. Figure 2 also shows that the application rate and the approval rate for the concessional loan programs are negatively correlated with the credit score in 2019. Figure 3 further show that the 2019 credit score and the loan amount are negatively correlated in general. The negative correlations are stronger for the concessional loans, especially made by Japan Financial Corporation and the private banks, than for the standard loans. These figures suggest that the firms with low credit scores are more likely to join the support programs. Correlation, however, does not imply causation. Thus, in the next section, we conduct regression analyses, controlling for the size of the COVID-19 shock to each firm and the heterogeneity of firms in terms of firm size, industry, and the region.

5. Pre-COVID-19 Credit Score and the Application and Receipt of Business Support Programs

5.1. Estimation Strategy

We now characterize the type of firms that tend to apply and receive the support grants and subsidies and concessional loans by conducting regression analysis. The dependent variable is a binary variable that takes the value one if the firm has applied for (or received) the government support. The explanatory variables are the credit score in 2019 and other controls, including sales growth during the pandemic, firm size, sales prospect for 2021, industry fixed effects (either 2-digit or 3-digit level), and prefecture fixed effects. The observation becomes smaller, primarily due to the lack of sales information.

It is crucial to control for the sales growth/decline because the liquidity support policies targeted those firms that experienced significant sales drop. The expected sales growth is reported by each firm as a part of our survey. We estimate the following linear regression model.

$$
\begin{aligned}
(Apply\ \ or\ \ Receive)_{ijk,2020} \\
&= \ \beta \cdot Credit\ \ Score_{ijk,2019} + f(MinSalesGrowth_{ijk}) \ + \ \gamma \cdot ln(Sales)_{ijk,2019} \\
&+ \delta \cdot ln(emp)_{ijk,2019} + \theta \cdot Expected\ \ Sales\ \ Growth_{ijk,2021} + \ Region_k \\
&+ \ Industry_j \ + u_{ijk,2020}, \qquad (1)
\end{aligned}
$$

where $Apply_{ijk,2020}$ indicates if the firm *i* in industry *j* in region *k* applied for the program in 2020, $Receive_{ijk,2020}$ indicates if the firm i in industry j in region k received the program, $Credit\ Score_{ijk,2019}$ is the credit score of firm *i* in 2019, $MinSalesGrowth_{ijk}$ is the minimum monthly sales growth between February 2020 and September 2020 relative to the same month in 2019, $ln(Sales)_{ijk,2019}$ is the natural logarithm of the amount of sales in 2019, $ln(emp)_{ijk,2019}$ is the natural logarithm of employment in 2019, $Expected\ Sales\ Growth_{ijk,2021}$ is the expected sales growth in 2021 relative to 2019, $Region_k$ is 47 prefecture fixed effects, and $Industry_j$ is industry fixed effects. Depending on specification, some terms may be omitted, the industry fixed effects are considered for 2- or 3-digit level, and the function *f* of *MinSalesGrowth* is assumed to be linear.

Because the dependent variables in our regression model are binary, the linear model such as (1) cannot be literary true. Here, we follow Wooldridge (2010, p.563) and interpret (1) as a linear projection of the binary dependent variable on the explanatory variables. Then, our estimation gives us consistent estimates of the parameters in the linear projection. We could use fixed effect logit or probit estimators under some assumptions, but in a specification like ours that includes many fixed effects, those estimators are often inconsistent.[14]

5.2. Estimation Results for the Employment Adjustment Subsidy

Table 2 reports the estimation result for the application to the Employment Adjustment Subsidy. Column 1 shows the estimated coefficients from the simple regression model that includes the credit score as the only explanatory variable. The estimated coefficient is -0.288, which implies that 0.1-point higher credit score reduces the application probability by about 3 percentage point. Recall that a quarter of the sample firms applied for the grant.

Column 2 specification adds firm size variables, expected sales growth in 2021 relative to 2019, and the minimum of year-to-year sales growth between February and September 2020 as explanatory variables.[15] The estimated coefficient on the credit score becomes even more negative, -0.522. The sign of estimated coefficients on the other explanatory variables are sensible.

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[14] For robustness check, we also estimated the variant of the two way Mundlak model to deal with multiple fixed effects. The results from this alternative estimation approach were not different from the OLS results in any significant way as reported in the Appendix E.

[15] We also estimated the regression models with the firm age as an additional explanatory variable, but the result did not change in any significant way.

Smaller firms, in terms of sales, are more likely to apply for the subsidy, while larger firms, in terms of the number of employees, are more likely to apply for the subsidy. This may be due to the amount of subsidy being proportional to the total payments to furloughed employees.

Notably, firms expecting higher sales growth in 2021 are less likely to apply for the employment adjustment subsidy. This may be because the firms that expect quick recovery of sales decides to continue keeping their employees on payrolls without furloughing. Finally, the firms that experienced a deep sales drop are more likely to apply for the subsidy. Thus, even taking into account the higher application tendency by firms with poor performance *during the pandemic*, the firms with poor prospect *before the pandemic* were more likely to apply.

Column 3 allows a more flexible functional form on the effect of *MinSalesGrowth*. In order to receive the employment adjustment subsidy, a firm, as a rule, must have suffered at least a 5% decrease in sales compared with the same month in the previous year. Similarly, in order to receive the business continuation grant, a firm must have suffered at least a 50% year-on-year sales drop. Thus, we may expect a discontinuity of the function f at *MinSalesGrowth* = -5% and -50%. However, other programs have different thresholds. To allow for a flexible functional form, we create bin dummy variables corresponding to [-1, -0.90], (-0.90, -0.80], …..(-0.10, 0.00], (0.00, 0.10), …., (-0.90, 1.00), (1.00, maximum], and include the set of bin dummy variables in the regression. In this specification, the estimated coefficient for the credit score is attenuated, but still larger, at -0.417, than the estimate in the simple regression model and statistically significant.

Column 4 adds 47-prefecture fixed effects to the Column 3 specification. Since cases of COVID-19 are concentrated around urban areas, allowing for regional heterogeneity is potentially important. The estimated coefficient on the credit score continues to be negative and statistically significant. The estimate is larger, at -0.476, than the one in Column 3, in absolute value. The significant change in the estimated coefficients suggests that there is substantial regional heterogeneity. Looking at estimated coefficients on prefectural dummies (not reported in the table), we find that firms located in urban areas are more likely to apply for the Employment Adjustment Subsidy. Since there is also a systematic difference in average credit scores across prefectures, a regression without prefectural dummies can result in biased estimates.

Finally, Columns 5 and 6 specifications add 2-digit and 3-digit industry fixed effects, respectively. The inclusion of the industry fixed effects reduces the estimated negative impact of the credit score on the likelihood of applying for the special term of the Employment Adjustment Subsidy. Thus, at least a part of the correlation between a low credit score and the high likelihood of applying for the grant is at industry level: an industry with more low-credit-score firms are more likely to have larger number of firms applying for the grant. As reported by Kikuchi, Kitao, and Mikoshiba (2020), the impacts of COVID-19 vary greatly across industries. Thus, it is not surprising that a part of the correlation we find comes from between-industry variation.[16] Even with industry dummies, however, the coefficient estimate on the credit score is negative. Whether we use 2-digit industry fixed effects or 3-digit industry effects seems to make little difference, -0.289 and -0.279 respectively, although it is statistically significant only at 10% level with 3-digit industry effects.[17]

5.3. Key Estimation Results for Various Programs

Below, we report the regression results for various government support programs, using the specification with prefecture fixed effects and 2-digit industry fixed effects (Column 5 specification). Thus, we focus on the within-industry variation of credit scores as of 2019 and examine the correlation between credit score and participation in the programs.

Table 3 tabulates the estimated regression coefficients on the credit score for different dependent variables. The other regressors in this table are the same as in Column 5 of Table 2, namely, ln(Sales of 2019), ln(Employment of 2019), Sales prospect of 2021 relative to 2019, bin dummy variables for the range of the minimum of the year-over-year sales growth between February and September 2020, prefecture fixed effects, and 2-digit industry fixed effects. The full regression results, with the exception of dummies and fixed effects, are reported in Appendices C and D.

To give an idea about the magnitude of these estimates, we consider the impact of a 0.1-point increase in the credit score on the application for, and approval by, each program. Because the sample average of the credit score is 0.543, with the standard deviation of 0.067, we essentially consider what happens when the credit score improves by 1.5 times the standard deviation.

The first row of Panel A in Table 3 reports the regression of the application to the various government grants and subsidies. The first row of Column 1 (application to the special terms of the Employment Adjustment Subsidy) just repeats the estimated coefficient reported in Column 5 of Table 2. The estimated coefficient is statistically significant at a 5% level. The 0.1-point increase of the credit score decreases the application probability by about 3 percentage points. This is a sizable impact, as the sample application rate is 26%, about a quarter.

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[16] Although we do not discuss it here, the government also introduced industry-specific subsidies, namely the Go-To Hojokin, a subsidy for the travel industry and restaurants, 1.7 trillion yen in total in two supplementary budgets. Tokyo prefecture was initially not included for this subsidy, due to a more severe pandemic situation. Apparently, prefecture fixed effects and industry fixed effects should be also effective to control for the omitted variable.

[17] We can go further and add the interaction term between the prefecture and the industry fixed effects. We have tried this with 2-digit level industry classification. This reduces the number of observations substantially because there are many cases where only one firm in a particular industry exists in a particular prefecture. The estimation result does not depend on whether we include the prefecture-industry specific effects or just prefecture and industry fixed effects.

For the Business Continuity Grant, the 0.1-point increase in the credit score decreases the application rate by about 3 percentage points. This is again sizable, as the sample application rate is 24%. For the Office Rent Grant, the 0.1-point increase in the credit score reduces the application rate by about 2 percentage points. This is relatively large, compared to the sample application rate of 10%. These estimates are statistically significant at a 5% level.

Similarly, we find that firms with a 0.1 higher credit scores are less likely to file for the Corporate Tax Moratorium and the Property Tax Reduction, about 4% and 1%, respectively. They are statistically significant at a 5% level for the former and at a 10 % level for the latter.

The second row of Table 3 reports the estimated coefficients for the credit score on the probability of receiving the business support programs. The column for the Corporate Tax Moratorium and the Property Tax Reduction is empty since the survey did not ask if the tax moratorium/reduction had been accepted. Tax moratorium/reduction applications are accepted as long as they are properly prepared. For the other programs, the survey asked if the firm actually received the support and some firms that applied for the support answered that they had not received the support. This does not mean, however, that their applications got rejected. Rather, these cases seem to reflect the time lag between application and receipt. As for the grants and subsidies, the government are supposed to approve all the valid applications. Valid applications for concessional loans are also likely to be approved almost automatically because those loans are 100% guaranteed publicly and expected to generate positive interest revenues for any banks. We thus estimate the regressions for the receipts, not to distinguish application from receipts, but to show that we get the same result whether we look at the applications for or the actual receipts of the support.

The estimated coefficients in the second row of Table 3 indicate that firms with a higher credit score are less likely to receive them, but the estimated coefficient is statistically significant only for the receipt of the Business Continuity Grant. The estimate implies that firms with a 0.1 lower credit score are 2.5 percentage points more likely to receive the Business Continuity Grant. It is a large effect considering that a bit more than 20% of sample firms receive this grant. In other words, a firm with a one standard deviation higher credit score is 7.7 % more likely to receive the Grant.[18] Overall, we find that firms with lower credit scores are more likely to apply for the government grants and subsidies, although the correlation becomes weaker when we look at actual recipient numbers .

We now turn to the regression results for the concessional loan applications, receipts, and the borrowing amount which are reported in Panel B of Table 3. For the applications to loans (special or

[18] The standard deviation of the credit score is 0.067, the estimated coefficient is -0.247, and the mean receipt rate is 0.215. Thus, 0.067*-0.247/0.215=-0.077.

standard) from JFC, Shoko Chukin, and private sector banks, the coefficient estimates on the pre-COVID-19 credit score are all negative and statistically significant at a 1% level. Thus, similar to the grants and subsidies, firms with low credit scores are more likely to apply for those loans. Moreover, the association is stronger for the concessional loans than for the standard loans from any sources.

For concessional loan programs by private sector banks, a firm with a 0.1-point decline in their credit score is about 10 percentage points more likely to apply. This is quite a large effect since about a quarter of the firms applied to these loans. In contrast, for standard loans from private sector banks, firms with a 0.1-point lower credit score are about 3 percentage points less likely to apply but it seems quite sizable considering only an 8% application rate.

The second row of Panel B of Table 3 shows the results for loan approvals. Here, we find that the firms with low credit scores are more likely to receive these loans. All the estimates are significant at least a 5% significance level. Specifically, a firm with a 0.1 lower credit score is about 6 percentage points more likely to receive the JFC concessional loan for which the sample receipt rate is merely 14%. In other words, a firm with a one standard deviation higher credit score is 28.1% more likely to receive the concessional loans from JFC.[19] The case for Shoko Chukin is a bit weaker with about half of the tendency for the JFC. The degree of the negative selection on the credit score is most severe in the special loan programs offered by the private sector banks, as is the case with application. A firm with a 0.1 lower credit score is about 8 percentage points more likely to receive those loans.

The third row of Panel B of Table 3 reports the regression results for the loan amount from banks, unconditional on application or receipt of the loans. In this unconditional analysis, those firms that do not borrow through a specific loan program are assigned zero values, whether or not they applied for the loan program. The dependent variable is the natural log of 1 plus the loan amount measured in 10 thousand yen. Adding 10 thousand yen to the loan amount is negligible in comparison to the average loan amount conditional on the receipt of loans. For example, Table 1 shows that the average concessional loan amount from JFC is about 60 million yen.

The first column shows the estimation result for the concessional loan program of JFC. A firm with a 0.1 lower credit score borrows about 0.5 log points more. The partial correlation between the credit score and the standard loan amount of JFC is smaller: a 0.1 lower credit score decreases the loan amount by about 0.15 log points. The third and fourth columns show the similar tendency for the loans made by Shoko Chukin with roughly a half effect for special loans, as well as standard ones. Overall, the results suggest that the two government lenders were more lenient on the concessional loans than the standard loans.

[19] The standard deviation of the credit score is 0.067, the estimated coefficient is -0.583, and the mean receipt rate is 0.139. Thus, 0.067*-0.583/0.139=-0.281.

For private banks, the result for concessional loans is very different from that for standard loans. The fifth column of Panel B of Table 3 shows that a firm with a 0.1 lower credit score borrows about 0.6 log points more concessional loan. In contrast, the corresponding number for standard loan is 0.2 log points. A firm with a one standard deviation lower credit score borrows concessional loans from private banks 0.14 log points more than from the JFC while it would get standard loans from private banks only 0.03 log points more than from the JFC. In summary, similar to the case with government financial institutions, the firms with lower credit scores before COVID-19 borrow larger amount from private banks, especially in concessional loans, and this tendency is much stronger for private banks.

The results, heretofore, show that the firms with lower credit scores are more likely to apply for and receive the concessional loans through both government and private banks. To quantify the degree at which financially unhealthy firms received the concessional loans, we calculate the total amount of the concessional loans made to the firms with credit scores below 0.5, that is, the firms TSR call for caution to give trade credits to its service subscribers. Table 4 tabulates the number of cases and the amount of loans given to such firms. Among all the concessional loans, 19% went to the firms with credit scores below 0.5. In terms of the loan amount, 18% of the total concessional loans went to such firms.

5.4. Discussions on Estimation Results

We find that the corporate supports including various grants, subsidies, and concessional loans during 2020 in Japan were more likely to have helped the firms with low credit scores. It is worth noting that our results do not necessarily show that the government supports were more likely to assist zombie firms, because a firm with low credit score is not necessarily a zombie. In the literature, a zombie firm is defined to be a firm that has poor performance *and* is subsidized by creditors and/or government so that it can stay in the market. Many papers including Caballero et al. (2008) look at the subsidization criteria only to identify zombies empirically.[20] Thus, the firms with low credit scores in our sample may not necessarily be zombies.

To see the relation between the credit score that we use and a standard measure of zombie, we identified those firms that are considered to have been zombies in 2019 following the approach

[20] Ignoring the corporate performance measures in identifying zombies is an intentional research strategy. Caballero et al. (2008) argued as follows. “We depart from past studies by classifying firms as zombies only based on our assessment of whether they are receiving subsidized credit, and not by looking at their productivity or profitability. This strategy permits us to evaluate the effect of zombies on the economy. If instead we were to define zombies based on their operating characteristics, then almost by definition industries dominated by zombie firms would have low profitability, and likely also have low growth. Rather than hard-wiring this correlation, we want to test for it.” (Caballero et al. 2008, p.1947)

used by Caballero et al. (2008).[21] In this approach, a firm is judged to be a zombie if the reported interest payment is below the "minimum required interest payment" that is inferred from the amount of borrowings and the going interest rates. For 2,465 firms in our sample, we have sufficient data to identify if they are zombies in this way. We then calculated the proportion of zombies among the firms with the same credit score. Figure 4 plots the proportion of zombie firms for each credit score. We clearly see that the firms with low credit scores are not necessarily zombies. In fact, for the firms with relatively low credit scores, the proportion of zombies rises as the credit score improves.

We can estimate a regression model using the zombie dummy instead of or in addition to the credit score, though the sample size becomes substantially smaller. Although we do not report the coefficient estimates here, we ran the regression and did not find that zombie dummy (as of 2019) influences the likelihood of receiving the government supports.

Combined with our main finding, the additional exploration using the zombie measures shows that the firms with low credit scores were likely to obtain the grants, subsidies, and concessional loans whether or not they were already zombies before the pandemic. The low credit score firms that were already zombies before the pandemic received more supports during the pandemic. Perhaps more importantly, the low credit firms that were not yet identified as zombies (we may call these "reserve army of zombies") before the pandemic may have become clear zombies by receiving supports during the pandemic.

Why were firms with questionable viability before the pandemic more likely to receive the government supports during the pandemic? The rest of this section considers four hypotheses and discusses how promising each one is.

First, a support program may have helped poorly performing firms, explicitly by design. That would be a case, for example, if the terms of a concessional loan (such as interest rates) are set favorably for the firms that were struggling before the COVID-19 pandemic. Glancing at the conditions for receiving the subsidies and the concessional loans, this possibility seems remote. We do not find any condition that would disproportionately favor the firms that did poorly *before* the pandemic. Almost all the conditions are about sales decline and other troubles that the firms encountered *after* the onset of the pandemic.

An exception is the special loans extended by private sector banks. As we discussed above, the special loans come with 100% guarantees by local Credit Guarantee Associations, which are eventually backed by taxpayers' money. Before the pandemic, the guarantee covered 80% of the loan

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[21] We use the zombie indicator calculated by one of the authors (Hoshi) and Toshihiro Okubo for a different research project. We thank Toshihiro Okubo for allowing us to use the series for this paper.

amount. Thus, banks were able to recover only 80% of the loan value in the event of bankruptcy. In other words, banks shared 20% of the loss. This presumably have prevented banks from taking too much credit risk. With a 100% guarantee, however, banks bear no cost of potential defaults. Hence, banks barely have incentives to differentiate viable firms from non-viable firms. This may lead private sector banks to provide the special loans to those firms that they would not lend if the loans were not fully guaranteed. If this were the case, it would not be surprising to find that poorly performing companies before the pandemic were more likely to apply for and receive the loans from private sector banks.

Second, even if a program does not explicitly favor poorly performing firms, it may have conditions that discourage applications by firms with good performance. This may apply for the concessional loans either by public or private institutions. For example, the firms that did well before the pandemic may enter the pandemic with more cash holdings and/or less debts than poorly performed firms. Moreover, firms with low leverage are less likely to gamble for resurrection. Thus, well performing firms may be less likely to apply for the concessional loans. On the other hand, this reasoning may not apply to the grants, subsidies, and special tax treatments that we look at. All these supports were gifts from the government to any firms that met the eligibility criteria, regardless of their financial conditions or leverage.

Third, grants, such as the Business Continuity Grant or the Office Rent Grant, were lump-sum transfers whose amounts did not depend on firm size. For such programs, large firms, which tend to have a high credit score, may not bother to apply. On the other hand, the amount of the Employment Adjustment Subsidy is set per worker and, therefore, the total amount is proportional to the number of employees. Thus, given a fixed cost of paperwork for program application, larger firms may have a stronger incentive to apply. This contrasting support-program designs seems to explain why the negative correlation of the credit score and the probability of receipt was stronger for the Business Continuity Grants than for the Employment Adjustment Subsidy.

Finally, there may be a reputational concern, similar to the one observed during the global financial crisis. Some banks were hesitant to accept any government bailout because they worried that accepting a bailout may signal a weakness of their balance sheets (Landier and Ueda, 2009 and Philippon and Skreta, 2012). Similarly, healthy firms may have decided not to apply for the subsidies or special loans out of concerns that applying would lead their banks, suppliers, and customers to suspect a weakness of their balance sheets. Also, hesitation may just stem from preference to avoid possible scrutiny on their balance sheets by banks and the government agencies (Balyuk, Prabhala, and Puri, 2021).

6. Robustness Check

This section reports three types of robustness check. First, we try an alternative measure of the firms' credit worthiness other than the credit score. Second, we restrict the sample to only those firms that satisfied the criteria on the decline in sales to be eligible for the public support programs. Third, we restrict the sample to the small and medium-enterprises (SMEs) defined in the SME Act of Japan.

6.1 Profit per Worker as an Alternative Measure of Creditworthiness

The analysis in the previous section used the TSR credit score as the measure for creditworthiness. Miyakawa et. al. (2017) and Miyakawa and Shintani (2020) report that the TSR credit score is a good predictor of firm exit, both bankruptcy and voluntary closure.[22] While we do not doubt the quality of TSR score as a creditworthiness measure, we would like to examine the robustness of our results using the monthly profit per worker figure as an alternative measure of the firms' creditworthiness before the outbreak of the pandemic.

We estimated the same set of models as those in Table 3 by replacing the TSR credit score by the monthly profit per worker. The results are reported in Table 5. The signs and statistical significance of the estimated coefficients are largely invariant to the change of the explanatory variable. The size of the estimated coefficient on the creditworthiness variable (i.e., profit per worker) substantially shrinks, but this merely reflects the fact that the level and the variance of monthly profit per worker is much larger than those of the credit score. Importantly, the firms with lower profitability are more likely to receive the government subsidy or grants. Those firms are also more likely to receive concessional loans from JFC, Shoko Chukin, and private banks. Moreover, all the coefficients are now statistically significant at least at the 10% level, except for the standard loan receipt from the JFC.

Overall, the analysis using the monthly profit per worker shows very similar results as above, that is, firms with lower profitability are more likely to take up the business support programs and concessional loans. Thus, our results are robust when we use an alternative measure of pre-pandemic performance of firms.

6.2 Subsample Analysis of Eligible Firms

As we discussed in Section 3, firms need to satisfy certain criteria to apply for the support programs. Many programs require the recipient firms to have suffered substantially during the pandemic. If the firms with low credit scores before the pandemic may have been more vulnerable to

[22] Both studies show that there is room for improvement through exploiting rich balance sheet information, combined with the variable section technique, based on machine learning algorithm.

the Covid-19 shock, our result can be explained as a simple reflection of eligible criteria imposed by the support programs. Our regression analysis control for the size of decline in sales during the pandemic, but this approach may not fully avoid the problem. Thus, we also estimated alternative set of regressions by limiting the sample to those firms that satisfy major conditions to be eligible for each support program (i.e., more than 5% sales decline from the same month of the last year for Employment Adjustment Subsidy, and Concessional Loan Programs; more than 50% sales decline from the same month in the last year for the Business Continuation Grant.).

Table 6 compares the regression results for the full sample and the sample of eligible firms for the Employment Adjustment Subsidy and the Business Continuity Grant. For the employment subsidy, the result for the subsample of eligible firms is qualitatively the same as that for the full sample. If anything, the coefficient on the credit score is slightly larger in magnitude. For the continuity grant, the estimated coefficient on the credit score gets smaller in magnitude when only the eligible firms are used. We note the sample size drops to about a quarter of the full sample and the standard errors increase substantially. The point estimate of the coefficient on the credit score is still negative but is not statistically significant.

Table 7 shows similar comparisons for concessional loans. Here the results for the sample of eligible firms are pretty much the same as those for the full sample. The estimated coefficients on the credit score are slightly larger in magnitude when the sample is limited to the eligible firms. Overall, the result does not change significantly when we use the sample of eligible firms only.

6.3 Subsample Analysis of SMEs

The sample in the previous section included all the respondent firms that we can find the necessary accounting data to allow the analysis, regardless of firm size. While most of the government support programs are open to all firms, many favor SMEs. For example, the maximum replacement rate of the employment adjustment subsidy for furloughed workers is 100% for SMEs, whereas it is 75% for larger firms. In the case of concessional loans by the two government banks, loan rates were 0.21% for SMEs and 0.46% for other firms for the first three years, and SMEs can receive subsidies to reduce the interest payments to effectively zero if they satisfy a certain set of conditions.

This differential treatment of SMEs may explain the negative relationship that we find between the credit score and the receipt of the support program. SMEs, with lower credit scores on average, may be more likely to apply and receive the supports than large firms, since the programs are designed to be more attractive to SMEs. To address this potential problem, we repeat the analysis using only SMEs as the regression sample.

The Small Business Act (*Chusho Kigyo Ho*) of Japan defines an SME by the number of employees and the stated amount of capital where the thresholds vary by industry.[23] Using the industry code, the number of employees, and the stated amount of capital in the TSR data base, we identify 3,867 SMEs out of 4,199 firms in our sample.

Table 8 reports the results of essentially the same regressions for Table 3 but are based on the restricted sample of the 3,867 SMEs. The coefficient estimates are almost identical to those in Table 3. Thus, the Table 3 results are not driven by a policy tendency to target SMEs.

7. Conclusion and Future Research

In examining the characteristics of the firms that applied for and received various subsidies and concessional loans that the Japanese government provided during the COVID-19 pandemic, we have found that the firms with poor performance (suggested by low credit scores) before the pandemic were more likely to receive those government supports. Within the analysis sample, about 20% of the total amount of concessional loans were lent to firms with credit scores in the “somewhat cautious” range (between 0.30 and 0.49). Not all of these firms were zombies before the pandemic. Thus, the government support programs seem to have protected some firms that were performing poorly but not yet overly assisted before the pandemic.

In the wake of the pandemic, swift supply of liquidity to the healthy but liquidity-constrained firms was necessary to prevent them from failing, and for that, a coarse screening might have been inevitable. However, policymakers need to realize that the generous liquidity provision also helped zombie firms and may have created new zombie firms. Such a policy may eventually transform the temporary shock due to COVID-19 into a permanent shock by distorting the liquidity supply toward inefficient firms.

It is also important to examine the benefit of the support programs. How effective these support programs were in protecting viable firms and productive employment relationships? We will be able to assess these policy impacts by comparing the actions of the firms that received supports to those of the firms that did not receive supports when the data for the post-pandemic period are available. We will of course need to control for the self-selection that we focus in this paper. We will also have to consider the general equilibrium impacts of the support programs. They may change the future behavior of the firms and the economy’s vulnerability to future shocks. For example, expectation for

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[23] To be classified as an SME, a firm has to be smaller than a certain threshold defined in terms of either the amount of capital or the number of employees. For the wholesale industry, the capital threshold is 100 million yen and the employee threshold is 300 employees. For the service industry, the thresholds are 50 million yen and 100 employees. For the retail industry, the thresholds are 50 million yen and 50 employees. For other industries, the thresholds are 300 million yen and 300 employees.

government grants could prompt the firms to hold less cash, make inflexible wage and/or employment commitments, and consider well-prepared business continuation plan, insurances for major disasters or even make bank credit lines unnecessary. One should also note that the social benefit of protecting businesses and/or employment is not entirely obvious. Business turnovers and job destructions are important parts of the dynamics that keep the economy growing. Claessens and Ueda (2020) builds a theoretical model that shows that preventing business closures and worker dismissal are socially desirable only when such a policy is not too generous and is the only way to maintain relation-specific capital and firm-specific skill. We leave a comprehensive evaluation of the government support programs for future research.

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Table 1: Descriptive Statistics

	Mean	SD
Baseline Characteristics as of December 2019		
Credit Score (Bad 0.0 – Good 1.0)	0.543	0.067
Profit / Worker and Month (1,000 JPY)	109	234
Sales / Worker and Month (1,000 JPY)	4,410	5,859
Sales (Million JPY)	5,383	15,331
Number of Employees	160	2,919
Experienced Shocks and Prospect		
Year-to-year Sales Growth of 2020 Relative to 2019		
February	-0.002	0.288
March	-0.021	0.307
April	-0.099	0.342
May	-0.141	0.345
June	-0.090	0.332
July	-0.090	0.316
August	-0.087	0.314
September	-0.076	0.306
Minimum of Sales Growth, February to September 2020	-0.305	0.302
Prospective Sales of 2021 Relative to 2019	-0.078	0.213
Business Support Programs or Leans	**Application**	**Receipt**
Special Terms of Employment Adjustment Subsidy	0.259	0.218
Business Continuity Grant	0.246	0.215
Office Rent Grant	0.102	0.065
Corporate Tax Moratorium	0.038	-
Property Tax Reduction	0.014	-
Concessional Loan by Japan Financial Cooperation	0.158	0.139
Standard Loan by Japan Financial Cooperation	0.038	0.030
Concessional Loan by Shoko Chukin	0.056	0.044
Standard Loan by Shoko Chukin	0.018	0.011
Concessional by Private Banks	0.254	0.229
Standard Loan by Private Banks	0.083	0.069
Receipt of Amount from Bailout Programs in 10,000 Yen	**Mean**	**SD**
Special Terms of Employment Adjustment Subsidy N=920	778	2,196
Business Continuity Grant N=906	399	1,106
Office Rent Grant N=281	251	267

Borrowing Amount in 10,000 Yen	**Mean**	**SD**
Special Loan by Japan Financial Cooperation N=595	5,893	6,467
Standard Loan by Japan Financial Cooperation N=131	6,700	8,604
Special Loan by Shoko Chukin N=194	9,322	9,021
Standard Loan by Shoko Chukin N=51	8,116	7,481
Special Loan by Private Banks N=971	5,029	5,380
Standard Loan by Private Banks N=292	13,477	18,713

Note: The number of observations is 4,201, except for profit where the number of observations is 3,856. Profit and sales related variables are winsorised at 1 and 99 percentiles. Application to the program and approval by the program are the indicator variables. The receipt variable is defined unconditional on application. The deadline for the application for tax or property tax holiday was April 16, 2020, which was in the early stage of the pandemic. The receipt amount of the bailout programs and the borrowing amount from banks are conditional on receipt.
Source: TSR-CREPE web survey, conducted between October 26 and November 6 of 2020.

Table 2: Determinants of Application for the Special Terms of the Employment Adjustment Subsidy

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.288***	-0.522***	-0.417***	-0.476***	-0.289**	-0.279**
	(0.101)	(0.126)	(0.124)	(0.128)	(0.130)	(0.133)
Ln (Sales of 2019)		-0.012*	-0.013*	-0.013*	-0.017**	-0.023**
		(0.007)	(0.007)	(0.007)	(0.009)	(0.009)
Ln (Employment of 2019)		0.062***	0.065***	0.064***	0.053***	0.057***
		(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
Sales Prospect of 2021		-0.152***	-0.147***	-0.150***	-0.120***	-0.099***
Relative to 2019		(0.034)	(0.034)	(0.034)	(0.033)	(0.034)
Min (YoY Sales Growth,		-0.282***				
Feb-Sep 2020)		(0.025)				
N	4,201	4,201	4,201	4,201	4,199	4,151
Bin Dummy Variables	No	No	Yes	Yes	Yes	Yes
of Min (Sales)						
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Note: Heteroskedasticity-consistent standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Some observations are dropped in Columns (5) and (6) because some industry exists only in one prefecture, which results in multi-collinearity. The average application rate for the special term of the employment adjustment subsidy is 0.256.

Table 3: Effect of Credit Score on Application to and Receipt of Grants, Subsidies, or Loans

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Program Type	Employment Adjustment Subsidy	Business Continuity Grant	Office Rent Grant	Corporate Tax Moratorium	Property Tax Reduction	
Outcome						
Application	-0.289**	-0.346***	-0.174*	-0.434***	-0.093**	
	(0.130)	(0.108)	(0.090)	(0.059)	(0.037)	
Receive	-0.174	-0.247**	-0.071	-	-	
	(0.125)	(0.108)	(0.076)			
Panel B						
Loan Type	JFC Concessional	JFC Standard	Shoko Concessional	Shoko Standard	Bank Concessional	Bank Standard
Outcome						
Application	-0.803***	-0.254***	-0.419***	-0.144***	-0.961***	-0.322***
	(0.113)	(0.062)	(0.073)	(0.042)	(0.132)	(0.088)
Receive	-0.583***	-0.171***	-0.339***	-0.081**	-0.758***	-0.231***
	(0.108)	(0.055)	(0.066)	(0.034)	(0.129)	(0.082)
ln (1 + Amt.)	-4.858***	-1.453***	-2.981***	-0.642**	-6.219***	-1.721**
	(0.902)	(0.459)	(0.578)	(0.294)	(1.071)	(0.722)

Note: N=4199. OLS estimates are reported. Heteroskedasticity-consistent standard errors are in parentheses. All specifications include bin dummy variables with 0.1 interval between -1 and 1 of minimum of sales growth between February and September 2020, natural logarithm of sales in 2019, natural logarithm of the number of employees in 2019, sale growth prospect of 2021 relative to 2019, prefecture fixed effects, 2-digit industry fixed effects. The approvals of corporate tax moratorium and property tax reduction are not recorded in the survey. Panel C reports the regression results of borrowing amounts conditional on receipt of the loans. The numbers of observations are different from Table 1 since some observations are dropped because of multicollinearity with fixed effects.

Table 4: Cumulative Borrowing Amount of Concessional Loans

	Cases	**Percentage**	**Cumulative Borrowing Amount**	**Percentage**
TSR Credit Score				
<=49	780	19%	18.68	18%
Total	4,201	100%	102.00	100%

Note: The sum of concessional loans made by Japan Financial Corporation, Shoko Chukin and Private Banks. Borrowing amount is in Billion Yen.

Table 5: Effect of Profit per Employee on Application to and Receipt of Grants, Subsidies, or Loans

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Program Type	Employment Adjustment Subsidy	Business Continuity Grant	Office Rent Grant	Corporate Tax Moratorium	Property Tax Reduction	
Outcome						
Application	-0.015***	-0.011**	-0.014***	-0.006**	0.002	
	(0.006)	(0.005)	(0.004)	(0.002)	(0.002)	
Receive	-0.013**	-0.010**	-0.008**	-	-	
	(0.005)	(0.005)	(0.003)			
Panel B						
Loan Type	JFC Concessional	JFC Standard	Shoko Concessional	Shoko Standard	Bank Concessional	Bank Standard
Outcome						
Application	-0.029***	-0.004*	-0.018***	-0.007***	-0.043***	-0.009**
	(0.005)	(0.003)	(0.003)	(0.002)	(0.006)	(0.004)
Receive	-0.023***	-0.002	-0.012***	-0.004**	-0.035***	-0.007*
	(0.005)	(0.002)	(0.003)	(0.001)	(0.006)	(0.004)
ln (1 + Amt.)	-0.195***	-0.018	-0.108***	-0.033**	-0.296***	-0.056*
	(0.039)	(0.020)	(0.026)	(0.013)	(0.047)	(0.033)

Note: N=3380. OLS estimates are reported. Heteroskedasticity-consistent standard errors are in parentheses. All specifications include bin dummy variables with 0.1 interval between -1 and 1 of minimum of sales growth between February and September 2020, natural logarithm of sales in 2019, natural logarithm of the number of employees in 2019, sale growth prospect of 2021 relative to 2019, prefecture fixed effects, 2-digit industry fixed effects. The approvals of corporate tax moratorium and property tax reduction are not recorded in the survey. The numbers of observations are different from Table 1 since some observations are dropped because of multicollinearity with fixed effects.

Table 6: Application to the subsidy programs, comparison of the full sample and the eligible firms

	(1)	(2)	(3)	(4)
	Employment Subsidy		Continuation Subsidy	
Credit Score	-0.289**	-0.307**	-0.346***	-0.276
	(0.130)	(0.150)	(0.108)	(0.298)
N	4199	3488	4199	1185
Bin Min Sales	Yes	Yes	Yes	Yes
Prefecture	Yes	Yes	Yes	Yes
2-Digit Ind	Yes	Yes	Yes	Yes
3-Digit Ind	No	No	No	No
Sample	All	-5% or less	All	-50% or less

Note: OLS estimates are reported. Heteroskedasticity-consistent standard errors are in parentheses. All specifications include bin dummy variables with 0.1 interval between -1 and 1 of minimum of sales growth between February and September 2020, natural logarithm of sales in 2019, natural logarithm of the number of employees in 2019, sale growth prospect of 2021 relative to 2019, prefecture fixed effects, 2-digit industry fixed effects. Column (1) reports the estimate from the full sample that reproduces the result reported in Table 3 Panel A Column (1). Column (2) reports the estimate from the eligible firm sample, the firms that experienced 5 percent or larger reduction in sales relative to the same month of the previous year in any single month. Column (3) reports the estimate from the full sample that reproduces the result reported in Table 3 Panel A Column (2). Column (4) reports the estimate from the eligible firm sample, the firms that experienced 50 percent or larger reduction in sales relative to the same month of the previous year in any single month.

Table 7: Application to the concessional loans, comparison of the full sample and the eligible firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Japan Financial Corporation		Shoko Chukin		Private Banks	
creditscore	-0.803***	-0.884***	-0.419***	-0.471***	-0.961***	-1.006***
	(0.113)	(0.130)	(0.073)	(0.084)	(0.132)	(0.152)
lnsales	-0.007	-0.008	0.011**	0.012**	-0.011	-0.016
	(0.008)	(0.009)	(0.005)	(0.006)	(0.009)	(0.010)
lnemp	-0.005	-0.008	0.011**	0.014**	-0.004	-0.004
	(0.008)	(0.010)	(0.005)	(0.006)	(0.010)	(0.012)
prospect	0.032	0.048	-0.011	0.005	-0.039	-0.019
	(0.029)	(0.036)	(0.019)	(0.023)	(0.034)	(0.042)
N	4199	3488	4199	3488	4199	3488
Bin Min Sales	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture	Yes	Yes	Yes	Yes	Yes	Yes
2-Digit Ind	Yes	Yes	Yes	Yes	Yes	Yes
3-Digit Ind	No	No	No	No	No	No
Sample	All	-5% or less	All	-5% or less	All	-5% or less

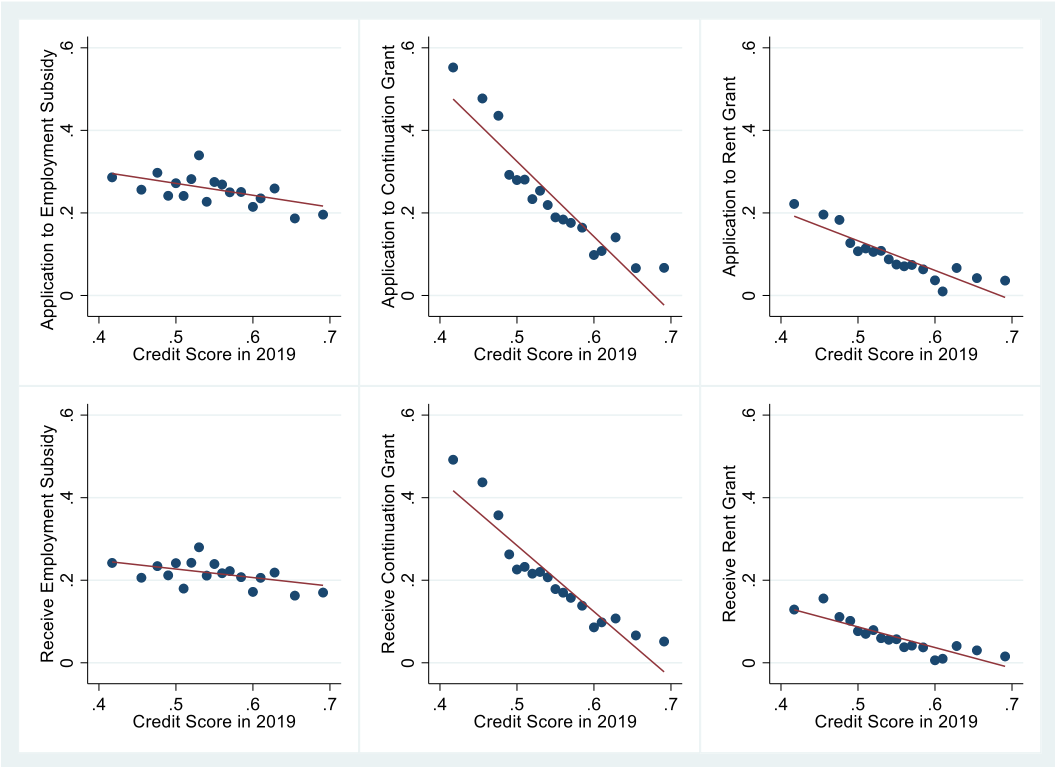
Note: OLS estimates are reported. Heteroskedasticity-consistent standard errors are in parentheses. All specifications include bin dummy variables with 0.1 interval between -1 and 1 of minimum of sales growth between February and September 2020, natural logarithm of sales in 2019, natural logarithm of the number of employees in 2019, sale growth prospect of 2021 relative to 2019, prefecture fixed effects, 2-digit industry fixed effects. Column (1) reports the estimate from the full sample that reproduces the result reported in Table 3 Panel A Column (1). Column (2) reports the estimate from the eligible firm sample, the firms that experienced 5 percent or larger reduction in sales relative to the same month of the previous year in any single month. Column (3) reports the estimate from the full sample that reproduces the result reported in Table 3 Panel A Column (2). Column (4) reports the estimate from the eligible firm sample, the firms that experienced 50 percent or larger reduction in sales relative to the same month of the previous year in any single month.

Table 8: Effect of Credit Score on Application to and Receipt of Grants, Subsidies, or Loans Among SMEs

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Program Type	Employment Adjustment Subsidy	Business Continuity Grant	Office Rent Grant	Corporate Tax Moratorium	Property Tax Reduction	
Outcome						
Application	-0.282*	-0.271**	-0.177*	-0.363***	-0.160***	
	(0.156)	(0.119)	(0.101)	(0.067)	(0.047)	
Receive	-0.168	-0.235**	-0.102	-	-	
	(0.152)	(0.118)	(0.084)			
Panel B						
Loan Type	JFC Policy	JFC Other	Shoko Policy	Shoko Other	Bank Policy	Bank Other
Outcome						
Application	-0.911***	-0.333***	-0.550***	-0.185***	-1.163***	-0.347***
	(0.132)	(0.074)	(0.095)	(0.053)	(0.155)	(0.108)
Receive	-0.664***	-0.252***	-0.434***	-0.113***	-0.957***	-0.254**
	(0.125)	(0.066)	(0.085)	(0.043)	(0.151)	(0.100)
ln (1 + Amt.)	-5.787***	-2.147***	-3.855***	-0.901**	-7.815***	-1.842**
	(1.083)	(0.564)	(0.761)	(0.375)	(1.272)	(0.901)

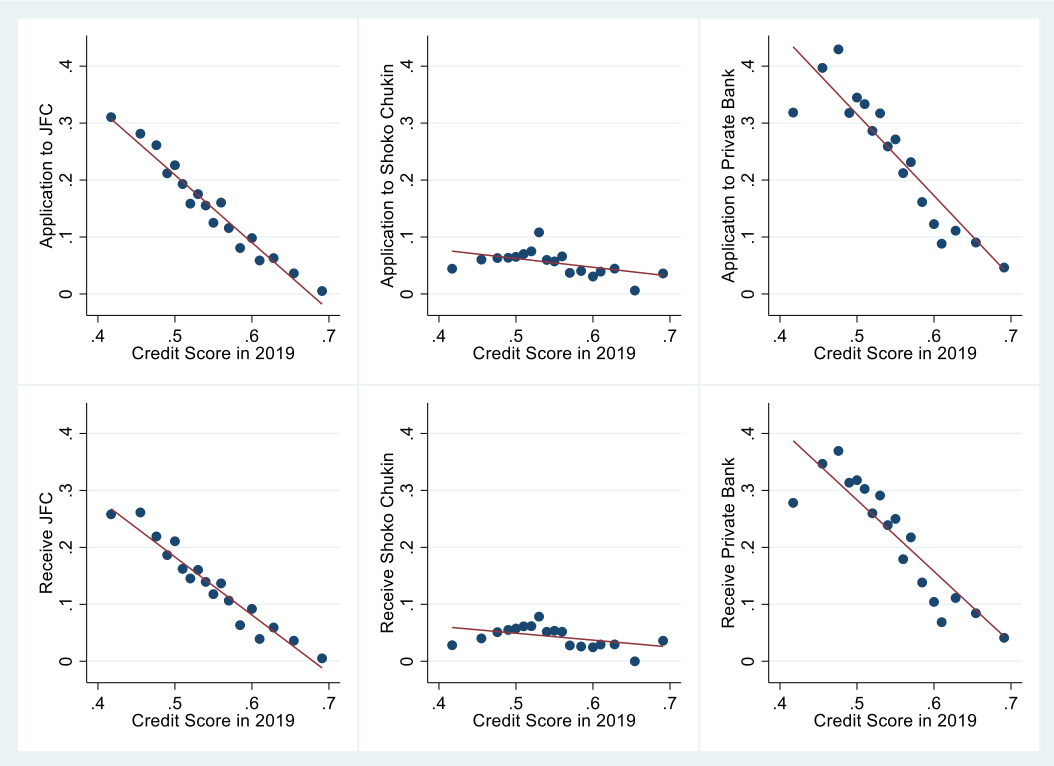
Note: The number of observation is 2,922 for all specifications. OLS estimates are reported. Heteroskedasticity-consistent standard errors are in parentheses. All specifications include bin dummy variables with 0.1 interval between -1 and 1 of minimum of sales growth between February and September 2020, natural logarithm of sales in 2019, natural logarithm of the number of employees in 2019, sale growth prospect of 2021 relative to 2019, prefecture fixed effects, 2-digit industry fixed effects. The approvals of corporate tax moratorium and property tax reduction are not recorded in the survey. The numbers of observations are different from Table 1 since some observations are dropped because of multicollinearity with fixed effects.

Figure 1: Credit Score in 2019 and Application and Receipt of Government Subsidies and Grants



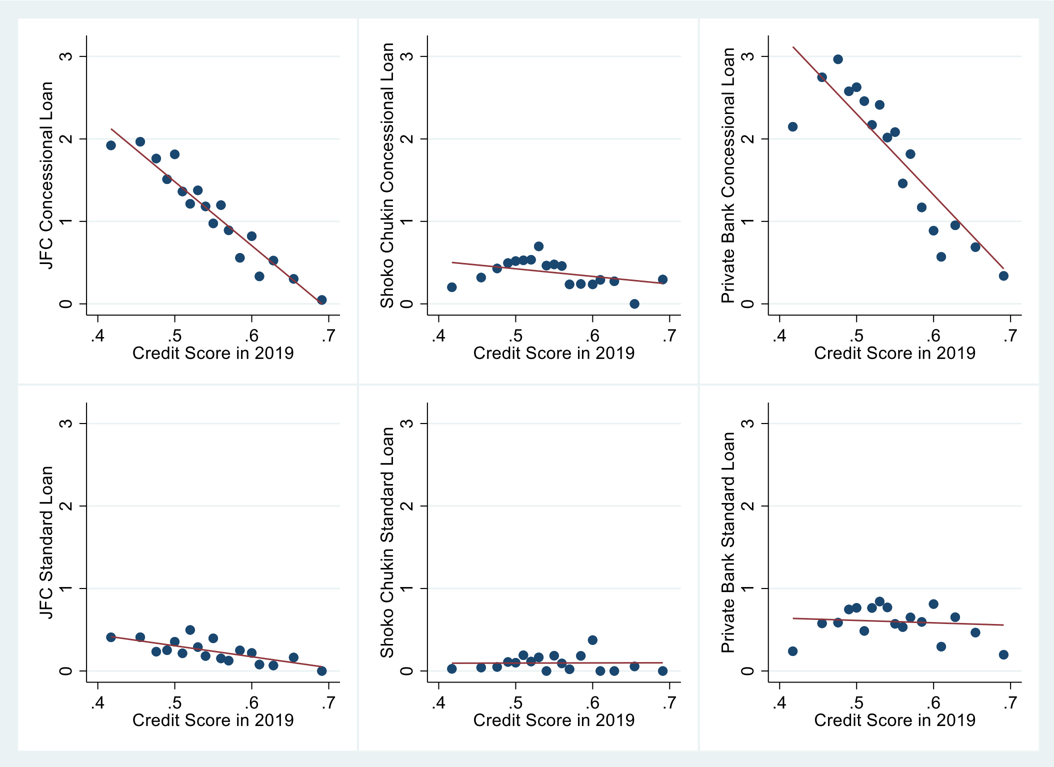
Note: Upper panels are for application to the subsidies and grants. Lower panels are for receipt of the subsidies and grants. The credit score is taken from the firm information file of TSR, as of December 2019. Application and receipt of the programs are taken from the TSR-CREPE firm survey. Each dot corresponds to the bin average of Y-axis. The straight line is the regression line estimated by OLS.

Figure 2: Credit Score in 2019 and Application and Receipt of Concessional Loans



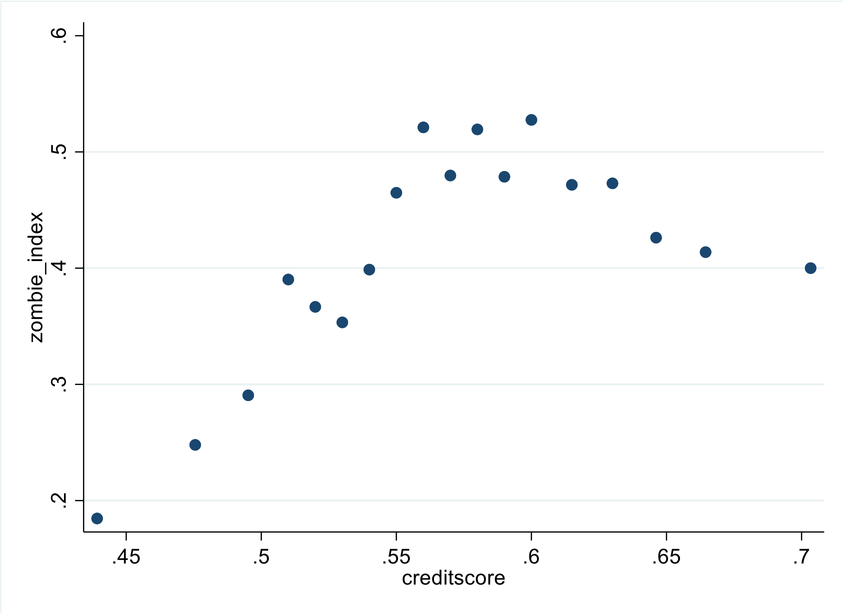
Note: Upper panels are for application to the concessional loan programs. Lower panels are for receipt of the programs. The credit score is from the firm information file of TSR, as of December 2019. Application and receipt of the programs are from the TSR-CREPE firm survey. Each dot corresponds to the bin average of Y-axis. The straight line is the regression line estimated by OLS.

Figure 3: Credit Score in 2019 and ln(1+ Borrowing Amount) of Concessional and Standard Loans



Note: All figures include only firms that applied and were approved for loans. Dependent variables are ln (1 + Borrowing Amount). Upper panels are for concessional loan programs. Lower panels are for standard loan programs. The credit score is from the firm information file of TSR, as of December 2019. The borrowing amount are from the TSR-CREPE firm survey. Each dot corresponds to the bin average of Y-axis. The straight line is the regression line estimated by OLS.

Figure 4: Credit Score in 2019 and the Fraction of Zombie Firm



Note: The credit score is from the firm information file of TSR, as of December 2019. Each dot corresponds to the bin average of Zombie firm dummy variable. Zombie firm is defined as the firm whose interest payment is below the minimum interest payment, which is the prime rate multiplied by the amount of outstanding debt. The sample is restricted to the firms that respond to TSR-CREPE firm survey.

Web Appendix

Appendix A: Questionnaire of the TSR-CREPE Special Firm Survey on the Effects of and the Reactions to COVID-19

The purposes of this survey are to examine the impact of the COVID-19 outbreak on firm operations and come up with effective policies. Your responses will not be used for other purposes except statistical analysis. Please answer about the situation at your company truthfully.

<u>Pre-COVID situation</u>

The following questions ask about the situation in 2019 before the spread of COVID-19 in Japan. Please refer to the situation at your company when the business operates normally.

Did your company have a Work from Home policy?

No, my company did not have a Work from Home policy.
Yes, my company had a Work from Home policy.

For those who answered, "yes" in the previous question, approximately what percentage of your employees were using the Work from Home policy and working remotely? Please answer by including employees who worked remotely even for a short period. However, please do not include employees working overtime at home due to, for instance, unfinished work, who were not under the Work from Home policy.

( ) %

Did your company have a pre-determined Business Continuity Planning (BCP), in other words, any usual operations or emergency plans to minimize the loss of company assets, and ensure the continuity of the main operation or quick recovery in the event of a disaster, such as natural disasters, fire, terrorist attacks, etc.?

No, my company did not have a BCP.
Yes, my company had a BCP.

For those who answered "Yes, my company had a BCP" in the previous question, was your company's BCP helpful during the outbreak of the COVID-19?

It was extremely helpful.
It was somewhat helpful.
It was not that helpful.
It was not helpful at all.

Forecast of the impact on sales and employment

How did the sales, number of employees (including part-time workers, contract workers, temporary agency workers), hours worked (overtime included) per employee of your company change in 2020? Please answer by comparing the numbers to those of the **same month in 2019**. For example, if there was no change, please answer "0", 15 percent increase, "15", 15 percent decrease, "-15".

	February	March	April	May	June	July	August	September
Sales								
Number of employees								
Average hours worked per person								

How do you think the sales of your company in 2021 (next year) are going to change compared to that of 2019 (last year)? If you think there will be no change, please answer "0", 15 percent increase, "15", and 15 percent decrease, "-15".

( ) %

Questions about firm operations under the Declaration of a State of Emergency

Between April 16th and May 25th, 2020, Japan had declared a State of Emergency for the whole country. Please answer the following questions by comparing the situation during the State of Emergency to that of January 2020, which was before the outbreak of the COVID-19.

What was your company's response to the work style of the employees during the Declaration of a State of Emergency? Please select all that apply.

My company made employees come to work as before.
My company let employees work remotely. Compared to the period before COVID-19, ( ) percent of the employees came to the workplace.
My company made employees take a temporary leave. My company made ( ) percent of the employees take a temporary leave.
My company dismissed employees. ( ) percent of the employees were dismissed.

Questions about the current work from home policy

The following questions ask about the present work style of the employees as of October 26, 2020. Please select all that apply. Please answer the questions by comparing the present situation with that in January 2020, which was before the outbreak of the COVID-19.

My company makes employees continue coming to work as before.
My company lets employees work remotely. Compared to before COVID, ( ) percent of workers come to the workplace.
My company makes employees take a temporary leave. ( ) percent of the employees are now taking a temporary leave.
My company has dismissed employees. ( ) percent of the employees have been dismissed.

Application and reception of assistance from the central and local governments

The central and local governments have been conducting several programs to aid the economic loss from the outbreak of COVID-19. Please select all of the programs that your company has applied for.

	Application (Yes/No)	Month of application (if applied)	Month of decision(if applied)	Amount of money (Ten thousand yen) (If rejected, please answer “0”.)
Employment adjustment subsidy				
Subsidy program for Sustaining Businesses				
Rent Support Funds				
Tax deferral/extension of payment deadline				—
Reduction or exemption of property tax etc.				—

Application and reception of assistance from financial institutions

The following questions ask about aid from financial institutions. Please select all of the aids your company has applied for.

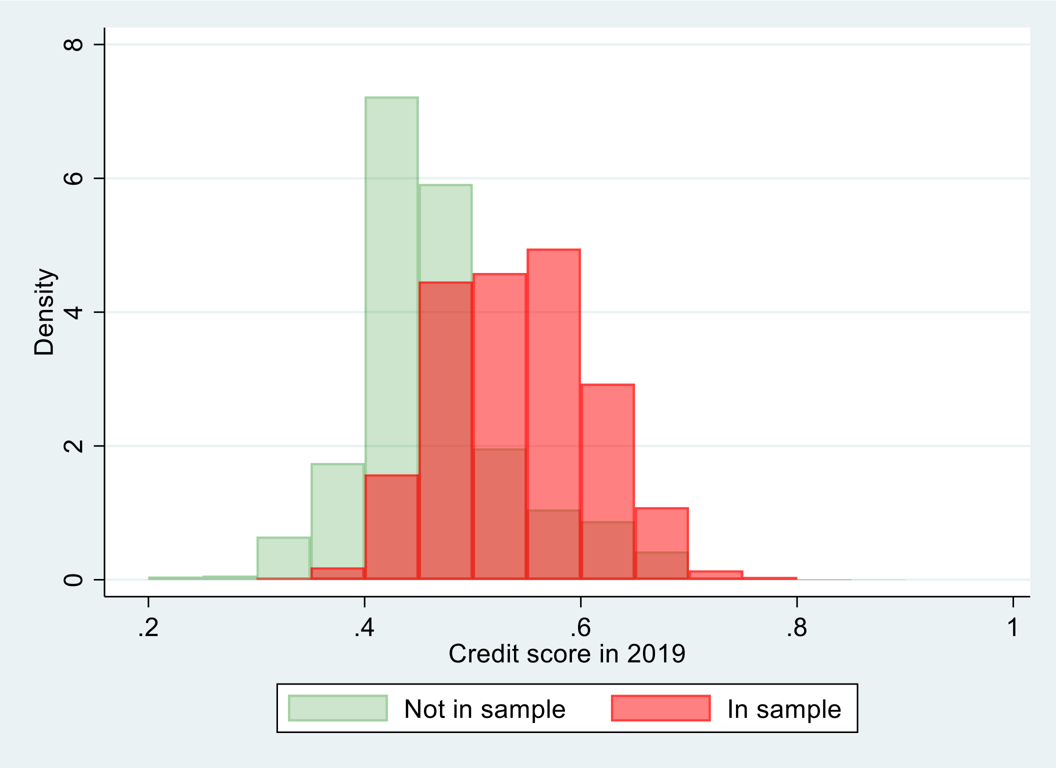
	Application (Yes/No)	Month of application (If applied)	Month of decision (If applied)	Amount of money (ten thousand yen) (If rejected, please answer "0".)
Zero-interest, collateral-free loan from the Japan Finance Corporation (Special Loan for COVID-19)				
Other loans from Japan Finance Corporation				
Zero-interest, collateral-free loan from the Shoko Chukin Bank（Disaster Recovery Loan）				
Other loans from the Shoko Chukin Bank				
Zero-interest, collateral -free loan from private financial institutions (with credit guarantee)				
Other loans from private financial institutions				

Appendix B: Characteristics of Survey Respondents Relative to the Firm's Population in the TSR Database

Appendix Table B1: Descriptive Statistics

	Population	**In sample**
Credit Score (Bad 0.0 – Good 1.0)	0.478	0.548
	(0.0758)	(0.0668)
Profit / Worker and Month (1,000 JPY)	50.23	103.7
	(201.6)	(215.5)
Number of Employees	25.26	173.1
	(420.3)	(2769.9)
SMEs	0.983	0.910
	(0.127)	(0.286)
Industry		
Agriculture, Forestry and Fishery	1.14	0.33
Mining	0.11	0.11
Construction	18.36	11.49
Manufacturing	10.82	29.61
Public Utility	0.34	0.27
Information	4.37	6.41
Transportation	2.24	4.70
Wholesale and Retail	21.23	26.20
Finance	1.80	0.98
Real Estate and Lease	8.52	3.41
Professional Services	7.83	5.85
Hotel and Restaurant	5.53	1.14
Life Services	2.93	1.54
Education	0.78	0.56
Health and Welfare	5.34	1.07
Postal Service and Cooperatives	8.33	6.34
Other Services	0.22	0.00
Public Sector	0.13	0.00
Total	100.00	100.00
N		

Appendix Figure B1: Distribution of Credit Score



Source: TSR data base as of December 2019 and TSR-CREPE special survey took place between October 26th and November 6th in 2020.

Note: The original credit score is divided by 100 in order to calculate the credit score above.

Appendix C: Detailed Regression Results of Program/Loan Applications

Table C1: Application to Business Continuity Grant

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Credit Score	-1.822***	-0.589***	-0.365***	-0.454***	-0.346***	-0.306***
	(0.095)	(0.110)	(0.101)	(0.105)	(0.108)	(0.112)
Ln (Sales 19)		-0.018***	-0.009	-0.007	-0.012	-0.013*
		(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
Ln (Emp 2019)		-0.033***	-0.031***	-0.031***	-0.032***	-0.032***
		(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
Prospect		-0.008	-0.049*	-0.045*	-0.040	-0.034
		(0.030)	(0.027)	(0.027)	(0.028)	(0.029)
Min (YoY S G)		-0.563***				
		(0.022)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C2: Application to Office Rent Grant

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.718***	-0.397***	-0.324***	-0.270***	-0.174*	-0.171*
	(0.069)	(0.085)	(0.084)	(0.087)	(0.090)	(0.093)
Ln (Sales 19)		0.004	0.008	0.004	-0.002	-0.003
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Ln (Emp 2019)		-0.009	-0.009*	-0.007	-0.004	-0.005
		(0.006)	(0.005)	(0.005)	(0.007)	(0.007)
Prospect		-0.029	-0.042*	-0.047**	-0.044*	-0.041*
		(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Min (YoY S G)		-0.282***				
		(0.017)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C3: Application to Corporate Tax Moratorium

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.443***	-0.462***	-0.440***	-0.452***	-0.434***	-0.409***
	(0.043)	(0.055)	(0.055)	(0.058)	(0.059)	(0.061)
Ln (Sales 19)		-0.005	-0.003	-0.003	-0.004	-0.007
		(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Ln (Emp 2019)		0.015***	0.015***	0.015***	0.016***	0.017***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Prospect		-0.043***	-0.046***	-0.046***	-0.044***	-0.046***
		(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Min (YoY S G)		-0.083***				
		(0.011)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C4: Application to Property Tax Reduction

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.078***	-0.105***	-0.091***	-0.111***	-0.093**	-0.086**
	(0.027)	(0.035)	(0.035)	(0.036)	(0.037)	(0.039)
Ln (Sales 19)		0.001	0.002	0.003	0.004	0.003
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Ln (Emp 2019)		0.004*	0.004*	0.003	0.001	0.000
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Prospect		0.006	0.006	0.007	0.012	0.013
		(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Min (YoY S G)		-0.047***				
		(0.007)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C5: Application to Concessional Loan of Japan Financial Corporation

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-1.187***	-0.892***	-0.843***	-0.934***	-0.803***	-0.805***
	(0.082)	(0.105)	(0.104)	(0.109)	(0.113)	(0.116)
Ln (Sales 19)		-0.006	-0.006	-0.002	-0.007	-0.006
		(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Ln (Emp 2019)		-0.002	-0.001	-0.001	-0.005	-0.005
		(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
Prospect		0.027	0.026	0.028	0.032	0.047
		(0.028)	(0.028)	(0.029)	(0.029)	(0.029)
Min (YoY S G)		-0.189***				
		(0.020)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C6: Application to Standard Loan of Japan Financial Corporation

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Credit Score	-0.247***	-0.275***	-0.273***	-0.294***	-0.254***	-0.255***
	(0.044)	(0.057)	(0.057)	(0.059)	(0.062)	(0.064)
Ln (Sales 19)		-0.001	-0.000	-0.000	-0.003	-0.002
		(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Ln (Emp 2019)		0.005	0.005	0.006	0.007	0.006
		(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Prospect		-0.025	-0.026*	-0.023	-0.025	-0.033**
		(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
Min (YoY S G)		-0.018				
		(0.011)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C7: Application to Concessional Loan of Shoko Chukin

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.155***	-0.443***	-0.414***	-0.466***	-0.419***	-0.417***
	(0.053)	(0.067)	(0.067)	(0.070)	(0.073)	(0.075)
Ln (Sales 19)		0.019***	0.019***	0.020***	0.011**	0.012**
		(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Ln (Emp 2019)		0.005	0.005	0.005	0.011**	0.010*
		(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
Prospect		-0.012	-0.011	-0.010	-0.011	-0.007
		(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
Min (YoY S G)		-0.071***				
		(0.013)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C8: Application to Standard Loan of Shoko Chukin

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.037	-0.160***	-0.159***	-0.171***	-0.144***	-0.166***
	(0.030)	(0.039)	(0.039)	(0.041)	(0.042)	(0.043)
Ln (Sales 19)		0.005**	0.005**	0.005**	0.001	0.003
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Ln (Emp 2019)		0.005*	0.005*	0.004*	0.008**	0.005*
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Prospect		0.005	0.005	0.005	0.006	0.008
		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Min (YoY S G)		-0.014*				
		(0.008)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C9: Application to Concessional Loan of Private Banks

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-1.429***	-1.020***	-0.944***	-1.086***	-0.961***	-0.913***
	(0.098)	(0.125)	(0.123)	(0.128)	(0.132)	(0.137)
Ln (Sales 19)		-0.006	-0.009	-0.000	-0.011	-0.017*
		(0.007)	(0.007)	(0.007)	(0.009)	(0.009)
Ln (Emp 2019)		-0.010	-0.007	-0.010	-0.004	0.002
		(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
Prospect		-0.067**	-0.061*	-0.053	-0.039	-0.052
		(0.034)	(0.034)	(0.033)	(0.034)	(0.035)
Min (YoY S G)		-0.179***				
		(0.024)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table C10: Application to Standard Loan of Private Banks

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.082	-0.343***	-0.320***	-0.332***	-0.322***	-0.263***
	(0.063)	(0.082)	(0.082)	(0.085)	(0.088)	(0.091)
Ln (Sales 19)		0.015***	0.016***	0.016***	0.013**	0.011*
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Ln (Emp 2019)		0.005	0.005	0.005	0.010	0.009
		(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Prospect		0.001	0.004	0.002	-0.006	-0.011
		(0.022)	(0.022)	(0.022)	(0.023)	(0.023)
Min (YoY S G)		-0.048***				
		(0.016)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Appendix D: Detailed Regression Results of Program/Loan Receipt

Table D1: Receipt of Employment Adjustment Subsidy

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.207**	-0.357***	-0.273**	-0.329***	-0.174	-0.157
	(0.095)	(0.120)	(0.118)	(0.122)	(0.125)	(0.128)
Ln (Sales 19)		-0.017**	-0.018***	-0.018***	-0.019**	-0.022**
		(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
Ln (Emp 2019)		0.057***	0.059***	0.058***	0.047***	0.049***
		(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
Prospect		-0.118***	-0.114***	-0.114***	-0.093***	-0.071**
		(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
Min (YoY S G)		-0.231***				
		(0.023)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table D2: Receipt of Business Continuity Grant

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-1.602***	-0.468***	-0.267***	-0.332***	-0.247**	-0.191*
	(0.091)	(0.108)	(0.100)	(0.104)	(0.108)	(0.112)
Ln (Sales 19)		-0.023***	-0.015***	-0.013**	-0.016**	-0.016**
		(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
Ln (Emp 2019)		-0.024***	-0.021***	-0.021***	-0.025***	-0.026***
		(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Prospect		-0.024	-0.063**	-0.058**	-0.057**	-0.049*
		(0.029)	(0.027)	(0.027)	(0.028)	(0.028)
Min (YoY S G)		-0.488***				
		(0.021)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table D3: Receipt of Office Rent Grant

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.500***	-0.237***	-0.191***	-0.122*	-0.071	-0.073
	(0.056)	(0.071)	(0.070)	(0.073)	(0.076)	(0.078)
Ln (Sales 19)		0.000	0.003	-0.001	-0.002	-0.002
		(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Ln (Emp 2019)		-0.007	-0.007	-0.006	-0.005	-0.005
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Prospect		-0.013	-0.021	-0.024	-0.026	-0.027
		(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
Min (YoY S G)		-0.185***				
		(0.014)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table D4: Receipt of Concessional Loan of Japan Financial Corporation

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-1.019***	-0.663***	-0.629***	-0.701***	-0.583***	-0.585***
	(0.078)	(0.100)	(0.100)	(0.104)	(0.108)	(0.111)
Ln (Sales 19)		-0.010*	-0.010*	-0.008	-0.009	-0.007
		(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Ln (Emp 2019)		-0.004	-0.003	-0.003	-0.010	-0.012
		(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Prospect		0.051*	0.052*	0.055**	0.061**	0.078***
		(0.027)	(0.027)	(0.027)	(0.028)	(0.028)
Min (YoY S G)		-0.161***				
		(0.020)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table D5: Receipt of Standard Loan of Japan Financial Corporation

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.176***	-0.170***	-0.174***	-0.196***	-0.171***	-0.167***
	(0.039)	(0.051)	(0.051)	(0.053)	(0.055)	(0.057)
Ln (Sales 19)		-0.002	-0.002	-0.003	-0.002	-0.003
		(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Ln (Emp 2019)		0.004	0.004	0.005	0.004	0.004
		(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Prospect		-0.019	-0.019	-0.018	-0.017	-0.022
		(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Min (YoY S G)		-0.012				
		(0.010)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table D6: Receipt of Concessional Loan of Shoko Chukin

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.121**	-0.336***	-0.321***	-0.353***	-0.339***	-0.330***
	(0.047)	(0.060)	(0.061)	(0.063)	(0.066)	(0.068)
Ln (Sales 19)		0.014***	0.013***	0.014***	0.008*	0.009**
		(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Ln (Emp 2019)		0.004	0.004	0.004	0.009*	0.008
		(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Prospect		0.007	0.007	0.007	0.008	0.012
		(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
Min (YoY S G)		-0.056***				
		(0.012)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table D7: Receipt of Standard Loan of Shoko Chukin

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.001	-0.099***	-0.098***	-0.099***	-0.081**	-0.084**
	(0.024)	(0.031)	(0.031)	(0.033)	(0.034)	(0.035)
Ln (Sales 19)		0.003*	0.003*	0.003*	-0.000	0.001
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln (Emp 2019)		0.004**	0.004**	0.004*	0.007***	0.006**
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Prospect		0.004	0.003	0.002	0.003	0.004
		(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Min (YoY S G)		-0.005				
		(0.006)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table D8: Receipt of Concessional Loan of Private Banks

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-1.254***	-0.832***	-0.765***	-0.884***	-0.758***	-0.685***
	(0.095)	(0.121)	(0.120)	(0.124)	(0.129)	(0.134)
Ln (Sales 19)		-0.007	-0.010	-0.003	-0.012	-0.018**
		(0.007)	(0.007)	(0.007)	(0.009)	(0.009)
Ln (Emp 2019)		-0.013	-0.009	-0.011	-0.010	-0.004
		(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
Prospect		-0.042	-0.037	-0.029	-0.017	-0.025
		(0.033)	(0.033)	(0.033)	(0.033)	(0.034)
Min (YoY S G)		-0.148***				
		(0.024)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Table D9: Receipt of Standard Loan of Private Banks

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.085	-0.264***	-0.245***	-0.252***	-0.231***	-0.159*
	(0.058)	(0.075)	(0.075)	(0.078)	(0.082)	(0.084)
Ln (Sales 19)		0.009**	0.009**	0.010**	0.008	0.003
		(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
Ln (Emp 2019)		0.005	0.005	0.006	0.008	0.010
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Prospect		-0.001	0.002	0.001	-0.004	-0.003
		(0.020)	(0.020)	(0.021)	(0.021)	(0.021)
Min (YoY S G)		-0.024				
		(0.015)				
N	4201	4201	4201	4201	4199	4151
Bin Min Sales	No	No	Yes	Yes	Yes	Yes
Prefecture	No	No	No	Yes	Yes	Yes
2-Digit Ind	No	No	No	No	Yes	No
3-Digit Ind	No	No	No	No	No	Yes

Appendix E: Comparison of the Estimates from the Linear Probability Model and the Average Marginal Effects of the Probit Model

We employed the linear probability model for the binary outcomes. To assess the robustness of the results, we estimate the following Mundlak style fixed effects model proposed by Wooldridge (2021):

$$Pr(Y_i = 1|X_i) \quad = \quad \Phi(X_i\beta + \bar{X}_{sales}\gamma_{sales} + \bar{X}_{ind}\gamma_{ind} + \bar{X}_{region}\gamma_{region}),$$

where Y_{it} is the binary dependent variable, X_{it} is the vector of independent variable, $\bar{X}_{sales}$ is the vector of means of independent variables by the sales change bins, $\bar{X}_{ind}$ is the vector of means of independent variables by the 2-digit industry category, and $\bar{X}_{region}$ is the vector of means of independent variables by the regions (47 prefectures). In this specification, the variation of X_i is used to identify β is the variation conditional on the means by sales change bins, industry, and region, thus virtually the within transformation is applied to each independent variable. The estimates of β obtained in this way are known to be consistent.

The following tables tabulate the OLS estimate of the coefficient on the credit score from the linear (projection) model and the average marginal effects of the credit score calculated from the random effects probit estimate. The OLS regressions use two fewer observations than the probit estimation because of multi-collinearity.

Table E1: Application to the Government Grants and Tax Treatments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Employment Adjustment Subsidy		Business Continuity Grant		Office Rent Grant		Corporate Tax Moratorium		Property Tax Reduction	
	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit
CS	-0.289**	-0.265**	-0.346***	-0.309***	-0.174*	-0.186**	-0.434***	-0.444***	-0.093**	-0.090**
	(0.130)	(0.131)	(0.108)	(0.112)	(0.090)	(0.090)	(0.059)	(0.066)	(0.037)	(0.038)
N	4199	4201	4199	4201	4199	4201	4199	4201	4199	4201

Table E2: Application to the Concessional Loan Programs

(1)	(2)	(3)	(4)	(5)	(6)
Japan Financial Corportation		Shoko Chukin		Private Banks	

	OLS	Probit	OLS	Probit	OLS	Probit
CS	-0.803***	-0.851***	-0.419***	-0.399***	-0.961***	-1.008***
	(0.113)	(0.115)	(0.073)	(0.073)	(0.132)	(0.134)
N	4199	4201	4199	4201	4199	4201

The comparisons of the OLS estimates and the probit estimates reveal that the differences in the estimates are 10 percent at maximum. Assuming that the two estimators are not correlated, none of the difference is statistically significant. Thus, our result is robust to an alternative specification that explicitly takes into account the non-linear property of the binary outcome model. We explain this in footnote 15 without showing this table.