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RESEARCH ARTICLE

Impact of financial support expansion on restaurant entries and exits during the COVID-19 pandemic

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Abstract This study examines the impact of an expansion of financial support to compensate for the business hour restrictions during the early COVID-19 pandemic on the entry of dine-in restaurants in the market. During this period, the local governments provided financial support to all restaurants to alleviate the urgent need for relief. This support was given regardless of their past performance, and it coincidentally provided an opportunity for new entrants that met certain criteria to receive support. Based on Japanese administrative data and a difference-in-differences estimation, our study shows that the expansion of financial support led to an increase in the number of dine-in restaurants. We also observed that the impact is more significant in areas with lower opening and operating costs, but it does not vary based on an index of potential sales. These results confirm that indiscriminate reduction of entry barriers could lead to the entry of less profitable and marginal new firms. Moreover, financial support led to a decrease in restaurant exits, especially of low-productive ones.

Plain English Summary During the early COVID-19 pandemic, Japan expanded its financial support for businesses to compensate for the business hour restrictions. Interestingly, this led to an increase in the number of restaurant openings despite the significant decline in demand. However, our analysis suggests that the expansion of financial support may have encouraged new entrants who were only interested in obtaining financial support, rather than having a long-term vision of providing better goods and services for customers. This suggests that reducing entry costs for all businesses during a recession may not be the most effective way to encourage new and desirable firms to enter the market. To prevent new and undesirable entrants from taking advantage of financial support, policymakers should consider providing financial support only to existing restaurants when business hour reductions are required. Alternatively, policymakers could set varying amounts of financial support based on sales, including for new entrants. It is worth noting that in Japan, although the amount of financial support was uniform across administrative districts, opening and operation costs varied. This created a situation where certain areas had a stronger incentive to enter the market.

Keywords COVID-19 · Entry and exit · Government support · Support during recession · Restaurant industry

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1 Introduction

Entrepreneurs and new firms are widely recognized as important contributors to economic growth and job creation, as evidenced by various studies (e.g., Audresch, 2007; Agihon et al., 2009; Baumol, 1968; Carree & Thurik, 2010; Haltiwanger et al., 2013; Urbano et al., 2019). However, economic downturns, such as the Great Recession, have a significant impact on their operations (e.g., Asturias et al., 2023; Dinlersoz et al., 2021; Fairlie, 2013; Gourio et al., 2016; Siemer, 2019). The COVID-19 pandemic has had a particularly negative impact on new firms, which are more vulnerable than established businesses. Consequently, the number of new business entries has significantly decreased during the early stages of the pandemic (e.g., Asturias et al., 2023; Dinlersoz et al., 2021; Sedlácek & Sterk 2020). To address this issue, many governments have implemented various forms of support for the affected businesses (Kuckertz & Brändle, 2022; OECD, 2020). It is important to analyze the impact of these support measures by considering how to assist new firms during economic recessions. In this study, we examine how the Japanese government's support for new entries in the restaurant industry affected their behavior during the early stages of the COVID-19 pandemic.

The COVID-19 pandemic and the subsequent lockdown policies severely affected the service industry, including restaurants. Early surveys conducted in the USA by Bartik et al. (2020) reveal that this industry is particularly vulnerable to prolonged economic shocks. In the UK, Barrero et al. (2020) also show that sectors requiring face-to-face service have shrunk. In 2020, the total sales of the restaurant industry in the USA were \$240 billion less than those estimated using pre-pandemic data for 2020 (National Restaurant Association, 2021). Japan also experienced a significant decline in household spending on eating out by 60% from April to May 2020 compared to that in the same period in 2019.[1] This is because the government asked people to limit their mobility from March 2020 onward to reduce contact with each other.[2] The government also requested that dine-in restaurants suspend overnight operations and reduce their business hours due to the risk of face-to-face contact increasing the rate of infection.[3] In view of implementing such a strict policy, the government decided to provide financial assistance to dine-in restaurants. This support policy started in April 2020 in Tokyo and other urban areas. Initially, the support amount was about JPY 25,000 ($\approx$ \$228.5) per day.[4] From December 2020 to March 2021, the amount of financial support was increased to 2.5 times the initial amount. Our primary focus is on the latter policy change, as it provides financial assistance to new businesses that meet certain criteria as well as existing restaurants. This gives us a unique opportunity to investigate the impact of such a policy on new enterprises.

Moreover, there are a few advantages of studying the policy impact on new firms. First, the policy was not specifically designed for new firms but to help existing restaurants. However, due to the urgent need for relief, the government provided financial aid to all businesses, regardless of their past performance. This resulted in potential new firms benefiting from this policy, which was an unexpected boost for them. After all, this is an entirely exogenous shock for these new firms and serves as a fascinating case study on the effects of financial aid on new businesses. Second, since every firm that suspended their overnight operations or shortened their business hours could receive support, this policy did not include any signaling effect. Government subsidy policies for new firms often involve screening, and recipients obtain subsidies, which signals that they are superior companies (Howell, 2017). Therefore, it is difficult to separate the impact of financial support from signaling firm performance. Finally, identifying the impact of such a specific policy is always challenging due to the government implementing various measures for small and medium-sized enterprises (SMEs) and self-employment. However, we can employ a difference-in-differences (DID) model because financial support for dine-in restaurants to compensate for their business

[1] Source: Family Income and Expenditure Survey in Japan.

[2] Some studies find that people stayed at home voluntarily, rather than due to government instruction (Goolsbee & Syverson, 2021, Watanabe & Yabu, 2021).

[3] The government deemed that dine-in restaurants are high-risk places where people spend longer periods of time and cannot use masks while eating and drinking.

[4] We used the June 11, 2021, central bank rate of USD/JPN 109.40 to convert JPY to USD. (https://www.boj.or.jp/statistics/market/forex/fxdaily/fxlist/fx210611.pdf)(accessed on June 11, 2021)

hour restrictions was implemented separately by local governments, making it easier to identify its effects.

We gathered data from administrative records covering newly approved restaurants as well as discontinued businesses in Japan. In accordance with the Food Sanitation Act, all restaurant owners must receive permission from a local public health center before opening and submit a notification of discontinuation before closing. We sourced these records by visiting each local government's website or requesting the data's release based on the Information Disclosure Ordinance. Our dataset comprised lists of restaurants that entered and exited before and during the COVID-19 outbreak. This allowed us to investigate changes in the number of entries and exits in the restaurant industry before and during the pandemic. Further, since our dataset encompasses all types of restaurants (dine-in and others) and multiple regions (with or without financial support), we used a DID model by business type and region to evaluate the causal effect of the financial support on dine-in restaurant entries and exits.

The findings are as follows. Our estimation results indicate that the expansion of financial support from December 2020 to March 2021 increased the number of dine-in restaurant openings and decreased the number of closings. Throughout fiscal year 2020 (FY2020), as compared to that in the pre-pandemic period, the number of restaurant openings remained consistent while the number of restaurant closings decreased. However, the results also indicate that the extent of the impact of the expansion was greater in areas with lower opening and operating costs, while it did not vary based on an index anticipating potential sales, which could have supported relatively low-productive firms or firms whose objective was to obtain the financial support. In addition, during the period when financial support expanded, among the dine-in restaurants that did exit, the proportion of those leaving within 1 year decreased substantially.

Our findings align strongly with previous studies that have highlighted the limitations of universal government aid for new firms in terms of economic performance (e.g., Branstetter et al., 2014; De Meza, 2002; Santarelli & Vivarelli2002). For instance, Branstetter et al. (2014) find that, although a regulatory reform reducing firm entry costs led to an increase in firm entries and employment in Portugal, most of these firms were "marginal firms" unlikely to survive the first 2 years. Shane (2009) also argues against indiscriminately supporting new entrants based on extensive previous study surveys. Our results support the view that, even during severe recessions such as the COVID-19 pandemic, governments should selectively support new firms. Therefore, policymakers need to reconsider support schemes for new firms during a recession. Further, previous studies also investigate the impact of government support programs on incumbent SMEs during the COVID-19 recession. Such support programs include subsidies, public credit guarantees, and emergency loans (e.g., Belitski et al., 2022; OECD, 2021; Honda et al., 2023; Liu et al., 2022; Pedauga et al., 2022; Yamori and Aizawa, 2021. Some studies have found that these programs have prevented exits of low-productive firms from the market (e.g., Belghitar et al., 2022; Block et al., 2022; Dörr et al., 2022; Honda et al., 2023; Hoshi et al., 2023; Morikawa, 2021; Muzi et al., 2023). Our findings support these previous studies, highlighting the importance of selective support by the government in keeping superior SMEs afloat during challenging economic times.

The remainder of this paper is organized as follows: Section 2 describes the government support for the restaurant industry; Sections 3 and 4 explain our data and estimation strategy, respectively; Section 5 presents the results; and finally, Sections 6 and 7 discuss the results and conclude the paper, respectively.

2 Institutional background

2.1 COVID-19 and government policies in the early pandemic period in Japan

In Japan, where the first confirmed COVID-19 case was reported in January 2020, in the earliest pandemic period, the increase in the number of cases was moderate, except for the cluster on the cruise ship Diamond Princess. As such, there was little impact on economic activities, at least until the end of February. In March 2020, the government asked people to stay at home and closed public schools. The first wave of the pandemic lasted from the end of March 2020 to May 2020 (Fig. 1).[5] To tackle the first wave, the first declaration of a state of emergency, as a request for people to voluntarily refrain from going out, was issued in April

[5] Figure 1 shows the trend of new COVID-19 cases across major cities.

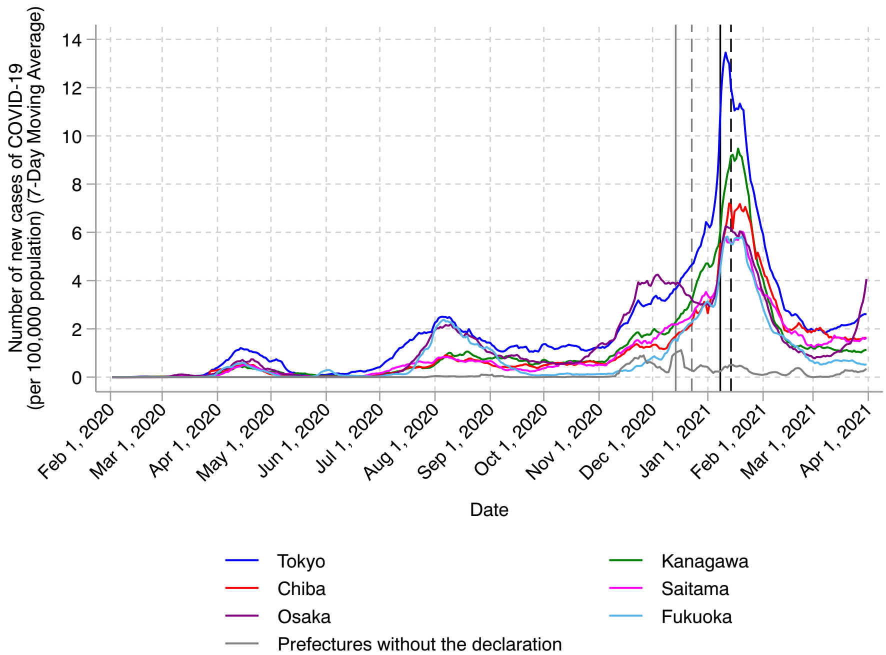


Fig. 1 Seven-day moving average number of new positive cases of COVID-19 (per 100,000 population). Source: Toyo Keizai Online "Coronavirus Disease (COVID-19) Situation Report in Japan." Notes: The gray solid line indicates December 14, 2020, when the prime minister announced that the national government will support local governments to expand the financial support for reducing the business hours of dine-in restaurants. The gray dashed line indicates December 23, 2020, when the chair of the subcommittee on the novel coronavirus disease control recommended the national government to take measures regarding businesses, including restaurants reducing their business hours in Tokyo. In addition, on December 25, 2020, the prime minister asked restaurants to reduce their business hours and receive financial support and/or penalties. The black solid line indicates January 8, 2021, when a state of emergency was declared in Tokyo, Kanagawa Prefecture, Chiba Prefecture, and Saitama Prefecture, and the black dashed line indicates January 14, 2021, when a state of emergency was also declared for seven prefectures, including Osaka and Fukuoka

2020. Around the same time, the local governments also asked a wide range of industries to refrain from business activities in Tokyo and other urban areas.

As the restaurant industry has been one of the industries significantly affected by the pandemic, government policies aimed at combating this impact since the onset of the first wave. Frequent infection clusters were observed at dine-in restaurants that served alcoholic beverages at night. As a result, restrictions on operating hours in dine-in restaurants were intermittently enforced. In addition, local governments encouraged people to avoid going out until the start of a campaign aimed at preventing cluster outbreaks. These restrictions and people's associated behaviors reduced the demand for restaurants in 2020. The expenses for eating out decreased after March 2020, reaching a decrease of around 56% compared to the average value from January 2016 to January 2020 in April 2020, and reached only the pre-pandemic level in March 2023 (Fig. 2).[6] After the end of the first wave, local governments did not request business hours restrictions for dine-in restaurants until the end of 2020, except in Tokyo.[7]

Some local governments provided financial support for dine-in restaurants to compensate for the loss of revenue due to the restrictions on operating hours during the early pandemic period.[8] During the earliest COVID-19 pandemic period, for instance, the Tokyo

[6] Figure 2 summarizes the change in eating-out expenses for two or more person households from January 2016 to June 2023, normalized using the average value from January 2016 to January 2020.

[7] Tokyo's governor used financial support to enforce this request from August to September due to the increase in the number of new cases of COVID-19 (the second wave).

[8] For example, from January 8, 2021, to March 21, 2021, dine-in restaurants in Tokyo were required to close by 8 p.m. If the restau-

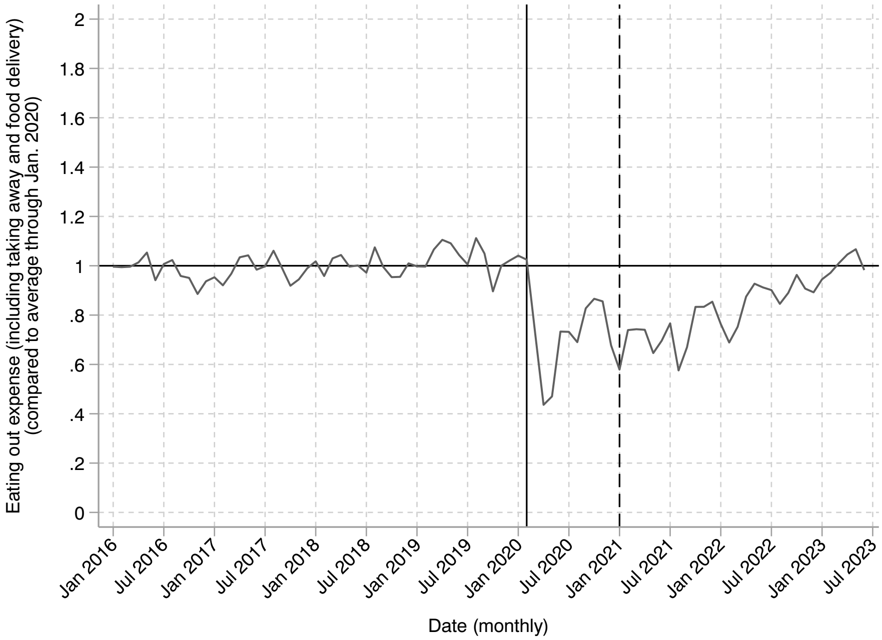


Fig. 2 Eating out expenses, including take away and delivery, (compared to the average value from January 2016 to January 2020). Source: Family Income and Expenditure Survey in Japan. Notes: The expenditure per household for two or more person households is used. To control for month-level seasonality, we regressed the eating-out expenses on month fixed effects and used the sum of residuals and the constant term as a seasonally adjusted eating-out expense. The average monthly seasonally adjusted expense per household through January 2020 is JPY 13,865. The solid and dashed vertical lines indicate February 2020 and January 2021

metropolitan government provided financial support for dine-in restaurants in response to the requirement of operating hour restrictions during the first wave (from the end of March 2020 to May 2020) and the second wave (from July 2020 to August 2020) of the pandemic. Similarly, Kanagawa Prefecture and Osaka Prefecture provided support during the first wave.

The central government of Japan provided financial assistance for SMEs and self-employed individuals operating before the pandemic, or incumbents, including running dine-in restaurants, through programs such as the Business Continuity Grant (*jizokuka kyufukin*) and the Office Rent Grant (*yachin shien kyufukin*).[9] Unlike these programs, the dine-in restaurants established after the onset of the pandemic could also apply for financial support aiming to compensate for the business hour restrictions. For example, in Tokyo, dine-in restaurants could apply for financial support as long as they started their business before the nighttime business restrictions were enforced.[10]

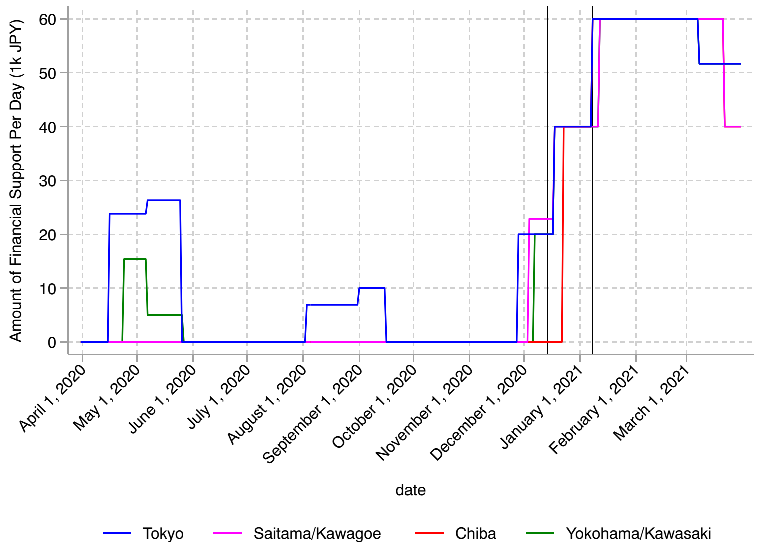
The payments varied across periods and municipalities. Figure 3 summarizes the amount of financial support per day for a dine-in restaurant if the restaurant fully cooperated with the request of local governments to reduce its business hours in the six prefectures in which the second state of emergency was declared (Fig. 4).[11] Since whether a restaurant could receive financial support depended on various conditions, for simplicity, the figure shows an example of the changes in the amounts for a dine-in restaurant with eligibility for all requests. Figure 3a covers four regions where the second state of emergency was declared on January

rants complied with this request, they were eligible to receive financial support.

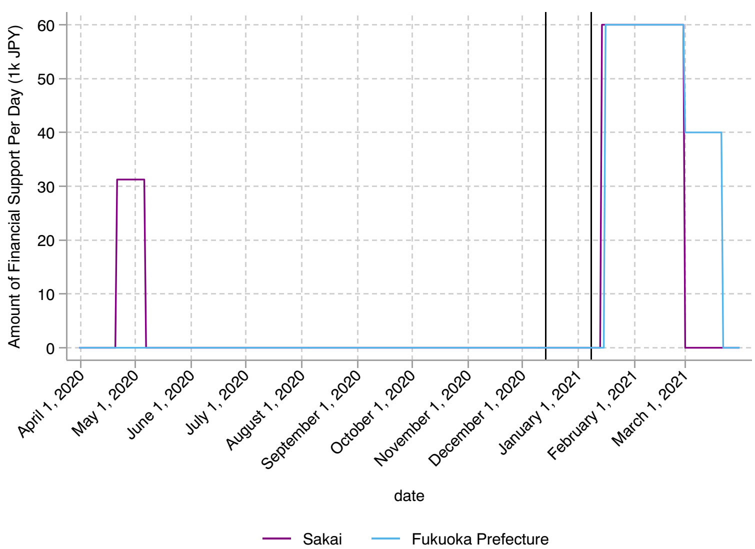
[9] The Business Continuity Grant and the Office Rent Grant were available for firms that had earned income in 2019 or earlier.

[10] In the case of the nighttime business restrictions between January 8, 2021, and March 21, 2021, in Tokyo, dine-in restaurants that started their business on January 7, 2021, could apply for financial support.

[11] We had access to the data in 6 of the 11 prefectures in which the second state of emergency was declared.



(a) Tokyo, Saitama/Kawagoe, Chiba, and Yokohama/Kawasaki



(b) Sakai and Fukuoka Prefectures

Fig. 3 Changes in the amount of financial support per day (JPY 1000). Notes: These figures summarize the amount of financial support per day for a dine-in restaurant that fully cooperated with the request by local governments to reduce business hours. Note that whether a restaurant could receive financial support depended on the address where the restaurant was located, even within the same prefecture. The first black line indicates December 14, 2020, when the prime minister announced that the national government would support local governments to expand the financial support for reducing the business hours of dine-in restaurants. Additionally, on December 23, 2020, the subcommittee on novel coronavirus disease control recommended the national government to take measures regarding businesses, including restaurants reducing their business hours in Tokyo, while on December 25, 2020, the prime minister announced the request for restaurants to reduce their business hours and receive either financial support and/or face penalties. The second black line indicates January 8, 2021, when a state of emergency was declared in Tokyo, Kanagawa Prefecture, Chiba Prefecture, and Saitama Prefecture. In addition, on January 14, 2021, a state of emergency was declared for other seven prefectures, including Osaka and Fukuoka

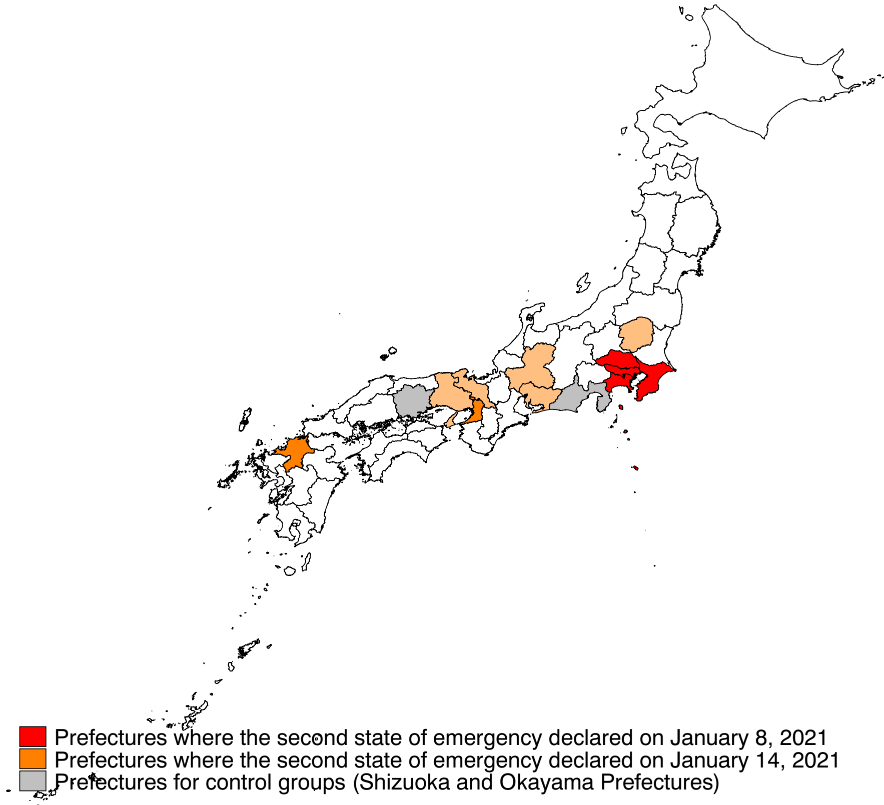


Fig. 4 Prefectures where the state of emergency was declared in January 2021. Notes: The dark colors indicate the prefectures with available data for analysis

7, 2021 (Tokyo, Saitama/Kawagoe, Chiba, and Yokohama/Kawasaki),[12] and Fig. 3b shows two regions in which the state of emergency was declared on January 14, 2021 (Sakai and Fukuoka Prefectures).[13] Figure 3 shows that the financial support for dine-in restaurants reducing their business hours before December 2020 in selected areas was characterized by small payment amounts and shorter periods. For instance, a restaurant in Tokyo could receive JPY 25,000 (≈ $228.5) per day between April and May 2020 for reducing its business hours, and a restaurant in Osaka prefecture could receive JPY 31,250 (≈ $285.7) per day from late April to early May.[14]

It is important to note other policies for the restaurant industry in 2020. During a period of temporary decline in COVID-19 infections, to stimulate demand for dine-in restaurants, the governments started a subsidy scheme for people using dine-in restaurants called the "Go to Eat" campaign. The campaign did not cover takeout and delivery-only restaurants. Therefore, this may have affected only the number of dine-in restaurant entries and exits. However, with the increase in the number of new infections, the campaign was terminated within 1 or 2 months. For example, the Tokyo metropolitan government started the campaign on November 20 and suspended it on November 26, 2020.[15][16] The expenses for eating out recovered somewhat during the "Go to Eat" campaign (October to

[12] Saitama and Kawagoe are cities in Saitama Prefecture, Chiba is a city in Chiba Prefecture, and Yokohama and Kawasaki are cities in Kanagawa Prefecture. Because whether a restaurant could receive financial support is based on its address, even within the same prefecture, the figure shows selected municipalities for each prefecture.

[13] Sakai is a city in Osaka Prefecture.

[14] We re-estimated the event study model by using the municipalities that provided financial support to dine-in restaurants reducing their nighttime business hours between April and May 2020 (Fig. 12). The estimation results do not show evidence of the significant impact of financial support between April and May 2020.

[15] https://www.maff.go.jp/j/shokusan/gaisyoku/hoseigoto.html(accessed on January 15, 2022)

[16]

People could buy the coupons for Go to Eat from November 20 to 26 in Tokyo, from November 6 to 24 in Kanagawa Prefecture,

Table 1 Financial support per month

	2020	2021			
	Dec.	Jan.	Feb.	Mar.	Subtotal (Jan.–Mar.)
Tokyo	900	1720	1680	1660	5060
Saitama/Kawagoe	880	1640	1680	1660	4980
Chiba	360	1720	1680	1660	5060
Kanagawa Prefecture					
Yokohama/Kawasaki	780	1640	1680	1660	4980
Other than Yokohama/Kawasaki	0	1200	1680	1660	4540
Osaka Prefecture					
Other than Osaka	0	1080	1680	0	2760
Fukuoka Prefecture	0	960	1680	840	3480

Notes: This summarizes the amounts of financial support per month for a dine-in restaurant that fully cooperated with the request of the local government to reduce its business hours. Whether a restaurant could receive financial support depended on the address where the restaurant was located, even within the same prefecture. This shows the amounts for all areas targeted by the requests of local governments. The unit is JPY 1000

November 2020) (Fig. 2). In later sections, we discuss the campaign's impact using descriptive statistics and estimations.

2.2 Expansion of financial support for dine-in restaurants after the end of 2020

The amount of financial support significantly increased after December 2020. For instance, in Tokyo, the amount per day between January and March 2021 was JPY 60,000, which was twice more than that between April and May 2020 and six times more than that between August and September 2020 (Fig. 3). In addition, the number of prefectures providing financial support increased among the six analyzed prefectures after December 2020 (Fig. 3). This is because, first, the number of new COVID-19 cases dramatically increased in December 2020 (Fig. 1). To reduce the rapid spread of infection, many municipalities started to ask dine-in restaurants to reduce their nighttime business hours, with financial support as compensation. Second, then Prime Minister Yoshihide Suga announced that the national government would financially support local governments in providing the compensation on December 14, 2020 (the first solid black line in the figure). Additionally, on December 23, 2020, the chair of the subcommittee on novel coronavirus disease control recommended the national government to take measures regarding businesses, including restaurants, to reduce their business hours in Tokyo (the second solid black line); 2 days after this recommendation, the then prime minister announced the legal basis for asking restaurants to reduce their business hours and obtain financial support and/or face penalties.

In practice, in all six prefectures, the amount of financial support for reducing nighttime business hours reached JPY 60,000 ($\approx$ \$548.5) per day after the state of emergency was declared. In the case of Tokyo, dine-in restaurants reducing their business hours could obtain financial support up to JPY 1.72 million ($\approx$ \$15,722) in January 2021 and JPY 5.06 million ($\approx$ \$46,252) from January 2021 to March 2021 (Table 1). According to a Japanese survey, during the pre-pandemic period, approximately 75.4% of dine-in restaurants reported monthly sales below JPY 1.8 million (equivalent to the monthly financial support amount of JPY 60,000 per day). This suggests that the daily support amount of JPY 60,000 can be considered substantial compared to the sales in the pre-pandemic period.[17] Between January and March 2021, the financial support amount was the same in each

from October 8 to November 27 in Chiba Prefecture, and from October 23 to November 27 in Saitama Prefecture.

[17] We used a sample between April 2018 and December 2019 to calculate the statistics of restaurant openings at ordinary times. The data source is the "Survey on Business Start-ups" conducted by the "Japan Finance Corporation Research Institute." Please see Appendix B.4 for more details.

prefecture. The opening and operating costs for dine-in restaurants can vary among municipalities within a prefecture, potentially creating a greater incentive to enter the market in areas with lower costs. In total, the budget for this support measure reached JPY 1 trillion ($\approx \$9 billion$) by January 2021.[18]

After the second state of emergency was lifted, the financial support amount was revised from a uniform amount to one based on the daily sales of individual restaurants. For example, in Tokyo, between April 12 and May 11, 2022, the amount per day ranged between JPY 40,000 and JPY 100,000 based on the daily sales of individual restaurants. For restaurants with daily sales below JPY 100,000, the support amount per day was fixed at JPY 40,000.[19] According to survey data, during the pre-pandemic period, 81.2% of dine-in restaurants earned below JPY 100,000 per day.[20] For most restaurants, the daily financial support amount was reduced by 33.3% from the original daily amount of JPY 60,000 to JPY 40,000, which reduced the incentive to enter the market.

After December 2020, while financial support for dine-in restaurants to reduce business hours was expanded, penalties were also established for dine-in restaurants that did not comply the hour reduction requests. If a restaurant did not comply, the prefectural governor could issue an "order" for the reduction. If the restaurant did not comply with the "order," the governor could impose a fine of up to JPY 300,000. Actually, the Tokyo Metropolitan Government notified the court to impose fines on four restaurants that refused to comply with the "orders" to reduce their business hours during the second state of emergency declaration from January to March 2021, and the court imposed fines of JPY 250,000 on each.[21] In sum, restaurants that did not follow the request faced monetary penalties, making it difficult for them not to accept the request. According to a survey conducted in the middle of January 2021, approximately 96.5% of restaurants responded that they would comply with the business hour reduction.[22]

3 Data

To investigate restaurant entries and exits during the pandemic, we used administrative data on newly approved licenses and the discontinuation of businesses in the food industry. In Japan, all food businesses, including restaurants, retail food businesses, and food manufacturers, need to obtain permission from the public health center of the local government. We used the list of these permissions, including information on business names, addresses, permission dates, types of businesses, types of applications (new or renewals), and closing dates.[23] We collected data in two ways: downloading them from the local government's website or asking each local government to provide data based on the Information Disclosure Ordinance. As many local governments did not publish the lists on their websites, we had to ask them for the data. We mainly focused on Tokyo and Kanagawa Prefecture, which declared a second state of emergency. Among the prefectures that declared the second state of emergency, Tokyo and

[18] According to an article published by Nihon Keizai Shinbun, an additional JPY 2 trillion ($\approx$ $18 billion) were allocated in February 2021 (https://www.nikkei.com/article/DGXZQODF0236H0S1A200C2000000/)(in Japanese)(accessed on October 3, 2023).

[19] The daily financial support amount was determined by multiplying the daily sales of individual restaurants by 0.4, with upper and lower limits set at JPY 40,000 and JPY 100,000, respectively. For restaurants with daily sales below JPY 100,000, the support amount per day was fixed at JPY 40,000 (lower limit), while restaurants with daily sales exceeding JPY 250,000 received JPY 100,000 (upper limit). For restaurants that opened within two months of April 12, 2021, we could calculate their daily sales based on the revenue earned from the opening date until April 11, 2021.

[20] The data source is the 2018 and 2019 "Survey on Business Start-ups" conducted by the "Japan Finance Corporation Research Institute."

[21] Please see the website of the Japan Broadcasting Corporation https://www3.nhk.or.jp/news/html/20210706/k10013122511000.html (accessed on August 3, 2023).

[22] The survey was conducted by INSHOKUTEN.com (https://www.inshokuten.com/research/company/), operated by Synchro Food Co., Ltd (https://www.synchro-food.co.jp/en). You can find the survey results: https://prtimes.jp/main/html/rd/p/000000431.000001049.html or https://www.inshokuten.com/research/result/252.

[23] When we analyzed the entrants into the restaurant market, we excluded those that applied to update their business licenses.

Table 2 Data sources

Departments in charge	Approved business licenses				Discontinuation of business				Format	Detailed info. on types of restaurants
	2017	2018	2019	2020	2017	2018	2019	2020		
Tokyo Metropolitan Government[1]	○	○	○	○					csv/excel	○
Shibuya[2]	○	○	○	○	○	○	○	○	csv/excel	○
Shinjuku	○	○	○	○	○	○	○	○	pdf	
Sumida	○	○	○	○	○	○	○	○	csv/excel	○
Taito	○	○	○	○	○	○	○	○	csv/excel	○
Bunkyo	○	○	○	○	○	○	○	○	csv/excel	○
Katsushika	○	○	○	○	○	○	○	○	pdf	
Koto	○	○	○	○	○	○	○	○	csv/excel	○
Nakano	○	○	○	○	○	○	○	○	pdf	
Toshima[3]		○	○	○		○	○	○	hardcopy	
Machida		○	○	○		○	○	○	csv/excel	○
Kanagawa Prefecture[4]		○	○	○		○	○	○	csv/excel	○
Yokohama	○	○	○	○	○	○	○	○	csv/excel	○
Kawasaki	○	○	○	○	○	○	○	○	csv/excel	○
Chiba[5]		○	○	○					csv/excel	
Saitama[6]			○	○					pdf	
Kawagoe[7]			○	○					pdf	
Sakai[8]		○	○	○					csv/excel	
Kitakyushu[9]	○	○	○	○	○	○	○	○	csv/excel	○
Kurume[10]	○	○	○	○	○	○	○	○	csv/excel	○
Shizuoka[11]	○	○	○	○					csv/excel	○
Hamamatsu	○	○	○	○					csv/excel	○
Okayama[12]	○	○	○	○					pdf	○

[1] The data cover the municipalities in Tokyo, except for the 23 special wards, Hachioji, and Machida, and are available at https://www.fukushihoken.metro.tokyo.lg.jp/iryo/hokenjo_daicho/shokuhineigyokyokadaicho.html
[2] The data are available at https://www.city.shibuya.tokyo.jp/kusei/tokei/opendata/index1.html
[3] We utilized OCR software to import the data
[4] The data cover the municipalities in Kanagawa Prefecture, except for Yokohama, Kawasaki, Sagamihara, Yokosuka, Fujisawa, Chigasaki, and Sabukawa The data on approved business licenses are available at https://www.pref.kanagawa.jp/docs/e8z/dst/s7561763.html We requested the use of the data on the discontinuation of businesses from the department in charge
[5] The data are available from August 2018 at https://www.city.chiba.jp/somu/somu/seisakuhomu/shisei/hokenjokankei.html#shokuhin
[6] The data are available at https://www.city.saitama.jp/008/016/001/008/p060481.html
[7] The data are available at https://www.city.kawagoe.saitama.jp/smph/jigyoshamuke/shokuhineisei/eigyokyoka/shokukaneiseiitiran.html
[8] The data are available at https://www.city.sakai.lg.jp/smph/kenko/shokuhineisei/anzenjoho/kyokashisetsuichiran/index.html
[9] The data on approved business licenses are available at https://ckan.open-governmentdata.org/dataset/401005_shokuhineiseihotokyokashisetsuichiran For data on approved business licenses for the years not listed on the webpage and data on business discontinuations, we requested their use from the department in charge
[10] The data on approved business licenses are available at https://data.bodik.jp/dataset/402036_0001500_00001 We requested the use of the data on the discontinuation of businesses from the department in charge
[11] The data are available at https://dataset.city.shizuoka.jp/dataset/shokuhin20151023-001
[12] The data are available at https://www.city.okayama.jp/kurashi/0000016508.html; they also cover 2014–2016

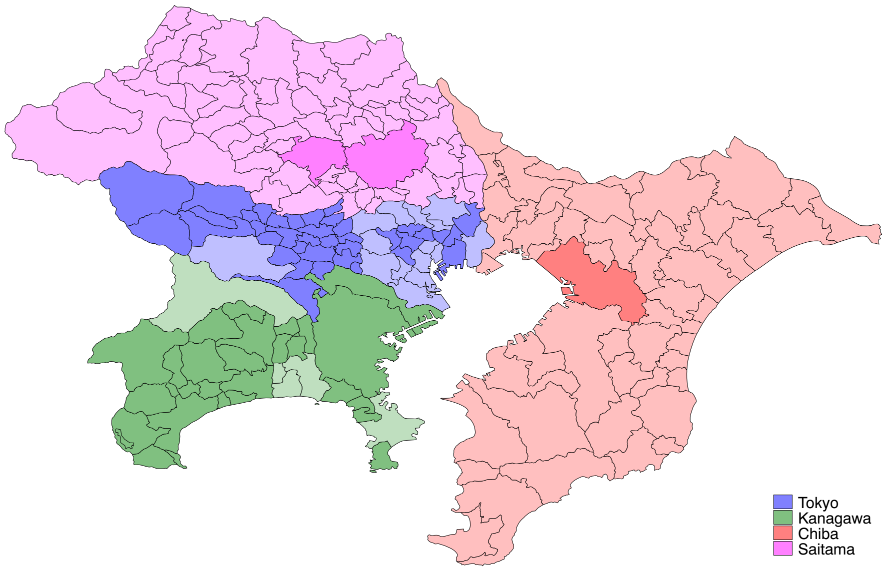


Fig. 5 Municipalities available for analysis in the Tokyo metropolitan area. Notes: The darker colored areas indicate the municipalities for which the lists of newly approved licenses for food businesses are available

Kanagawa Prefecture covered 45.5% of dine-in restaurants (in 2019)[24] and 33.1% population (in 2020)[25]

Table 2 summarizes the departments in charge of food businesses, types of data available, and available years. Overall, we obtained data on restaurants opening from 84 municipalities and on restaurants closing from 39 municipalities. Features of the data such as the years in which the data are available and format differed across departments in charge. For example, the data on Toshima were provided in hard-copy format, and we utilized the OCR software to convert them to a more manageable format. The notes to Table 2 explain the data features. Figure 5 shows the available municipalities in the Tokyo metropolitan area. The darker colored areas indicate the municipalities for which data on newly approved for food businesses are available. For Tokyo and Kanagawa Prefecture, data for around 76.8% (73 of 95) of municipalities are available. In addition, we collected data on six large cities in the prefectures that declared a second state of emergency (Saitama, Kawagoe, Chiba, Sakai, Kitakyushu, and Kurume) and three large cities in the prefectures that did not declare the second state of emergency (Shizuoka, Hamamatsu, and Okayama). For some municipalities, data on the discontinuation of food businesses are available, and we used them in the analysis. It is possible that some restaurants did not submit a notification of discontinuation, resulting in under-reporting.

The municipalities can be divided into three groups: the first group under the second declaration of state of emergency from January 7, 2021 (Tokyo, Kanagawa Prefecture, Saitama, and Chiba), the second group from January 14, 2021 (Sakai, Kitakyushu, and Kurume), and the third group not under the second declaration of a state of emergency (Shizuoka, Hamamatsu, and Okayama). Since the municipalities in the last group have similar population composition, we utilize them as the control group.[26]

In Table 3, the number of newly opened restaurants in the sample is above 20,000, and the restaurants that have gone out of business are around 12,000 in both FY2019 and FY2020.[27] The numbers in FY2020 are

[24] We calculated the proportion using the 2019 Report on Public Health Administration and Services (https://www.e-stat.go.jp/stat-search/file-download?statInfId=000032045165&fileKind=1). Among the whole of Japan, Tokyo and Kanagawa Prefecture covered 27.60% of dine-in restaurants.

[25] We calculated the proportion using the 2020 Population Census.

[26] Appendix B.1 discusses the difference in demographic characteristics between the municipalities under the second declaration of the state of emergency and those not under it.

[27] In some cases, food businesses apply for multiple types of licenses simultaneously. For example, if a restaurant plans to offer both dine-in and takeout services, it is necessary to obtain a license for in-store dining and one for food sales. After approval, the list of newly approved for food businesses includes the two approvals independently. As such, the number of newly approved business licenses is not necessarily consistent with the number of food businesses obtaining permissions. In this paper, when a food business obtains multiple business permissions on the

Table 3 Brief data description

	(1) Newly approved restaurants	(2) Restaurants have gone out of business
Total number by fiscal years		
FY2019: Apr. 2019–Mar. 2020	21,900	11,767
FY2020: Apr. 2020–Mar. 2021	21,315	11,963
Number of available municipalities	82	39

comparable to those in FY2019, despite the COVID-19 pandemic: a decrease of 3% and an increase of 1.7% for new approvals and discontinuations, respectively.

As explained in Section 2, the financial support for reducing business hours was only for dine-in restaurants; as such, we categorized the sample by business type. We utilized the information on types of approved businesses to classify food businesses into dine-in restaurants, other types of restaurants, including those serving foods only for takeout and for delivery and convenience stores.[28] All dine-in restaurants were eligible to apply for support in the prefectures providing support programs while takeout restaurants, delivery chains, or convenience stores were not. Therefore, we focus on two groups: dine-in restaurants as the treatment group and other types of restaurants as the control group.

We constructed a municipality-restaurant type level monthly dataset to identify the effects of the financial support for reducing business hours on the number of newly approved dine-in restaurants. Namely, we aggregated the number of newly approved restaurants by the municipality and restaurant type (dine-in/other types) for each month of FY2019 and FY2020 for which data are available for all municipalities. We considered the municipalities with at least one approved restaurant for both dine-in and other types in the two fiscal years; two villages in Tokyo, To-shima and Mikurajima, were excluded from the analysis. The number of observations is 3936 (82 municipalities $\times$ 2 types $\times$ 24 time periods). In the same manner, we also constructed the municipality-restaurant type level monthly dataset for restaurant closings, and the number of observations is 1872 (39 municipalities $\times$ 2 types $\times$ 24 time periods).

3.1 Descriptive statistics

This section presents the descriptive statistics of munici pality-wise restaurant types in terms of market entries and exits during each month of the COVID-19 pandemic. Table 4 shows the average monthly number of newly approved restaurants and that of restaurants that have gone out of business, as well as the proportion of non-zero observations for those numbers. According to Table 4, on average, around 11 restaurants obtained business approval per month, and around 70% of observations had at least one newly approved restaurant. Over the sample period, on average, around 13 restaurants went out of business. The number of dine-in restaurants with new business licenses is on average approximately 2.6 times more than that of other types of restaurants, and the same tendency is observed for restaurant closings. The average number of newly approved restaurants and that of restaurants that have gone out of business in FY2020 are almost the same as those in FY2019 (columns 2 versus 3), implying that new restaurant openings did not decrease and the closing of existing ones did not increase, despite the COVID-19 pandemic decreasing the demand in the restaurant industry.

The differences in the number of market entries and exits before and during the pandemic may be heterogeneous by month because the number of COVID-19 cases and the government's response to it changed dramatically every month. Figure 6 shows the number of newly approved dine-in restaurants in FY2020 (panel a) and that of dine-in restaurants that went out of business (panel b) compared to the same months in the previous year by category: April and May, November, December to next March, and other months. In FY2020, the first

same day, we consider those as one approved food business. We utilize information such as the name of the store, address, name of the person in charge of the store, and name of the owner to identify each business entity. This enables us to interpret the list of newly approved businesses as food businesses obtaining business permission.

[28] Appendix A.1 presents the types of restaurants.

Table 4 Summary statistics

	(1) Whole	(2) FY2020	(3) FY2019	(4) Dine-in	(5) Other types
Number of newly approved restaurants	10.98	10.83	11.13	15.86	6.10
	(25.62)	(25.21)	(26.03)	(29.47)	(19.94)
Proportion of non-zero observations	0.70	0.71	0.70	0.79	0.62
	(0.46)	(0.45)	(0.46)	(0.41)	(0.49)
Number of restaurants that have gone out of business	12.68	12.78	12.57	16.92	8.43
	(27.78)	(27.79)	(27.78)	(27.34)	(27.58)
Proportion of non-zero observations	0.70	0.70	0.71	0.79	0.62
	(0.46)	(0.46)	(0.46)	(0.41)	(0.49)

Standard deviations are shown between parentheses

financial support for restaurants to reduce their business hours was provided in April and May, the Go To Eat campaign was held in November, and financial support was expanded from December to the next March. In other months, there were few support programs for dine-in restaurants.

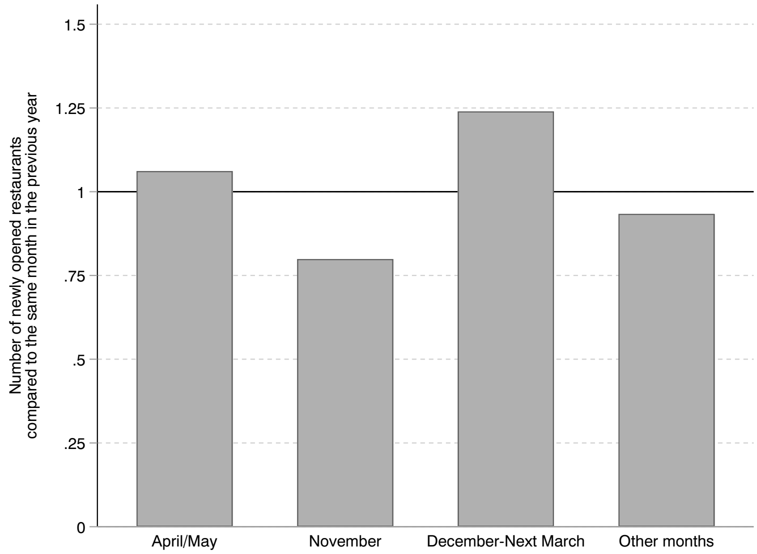
According to Fig. 6a, the number of newly approved dine-in restaurants was comparable with that in the same months of the previous year for April and May (1.06 times more). The number of newly approved dine-in restaurants from December to next March, when the financial support expanded to other prefectures and included larger amounts, was approximately 1.24 times more than that in the same months in the previous year despite all prefectures facing the highest number of new COVID-19 positive cases in FY2020. The number of newly approved dine-in restaurants in November, when the Go To Eat campaign was held, was around 80% of that in the previous November; in other months, the number of newly approved dine-in restaurants in FY2020 was smaller than that in the same months in FY2019. The result suggests that the financial support for dine-in restaurants to reduce their business hours offsets the decrease in entries due to the pandemic, and the larger amount of financial support from December to next March had an important role in promoting new entrants.

The number of restaurants that went out of business during the months with support programs was below that in the previous year (from right to left, 88.3%, 88.6%, and 96.4%) (panel b). In other months, the restaurant closings in FY2020 were 120% more than those in FY2019. Unlike restaurant openings, the number of restaurant closings might have been affected by the Go To Eat campaign. As the campaign aimed to encourage people to eat at dine-in restaurants and the restaurants could get a subsidy as well, the campaign might have prevented the restaurants that wanted to continue businesses from closing, but it did not promote restaurant openings for the subsidy only.

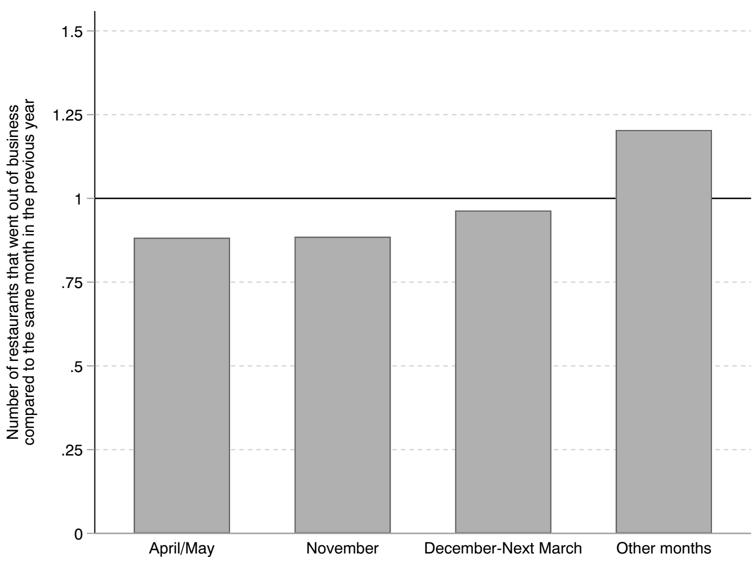
While the descriptive statistics suggest that supportive measures, particularly the expansion of financial support for dine-in restaurants reducing their business hours, affected restaurant openings and closings, we cannot rule out other factors that influenced restaurant openings and closings. For example, there were other government policies for all firms. Further, it is possible that after December 2020, the promotion of entries and the suppression of exits due to financial support were offset by the significant increase in the number of COVID-19 cases. To evaluate the impact of the expansion of financial support more accurately, we employ an event study and DID models.

4 Estimation

While there is an increase in the number of newly approved restaurants and a decrease in the number of closing restaurants after the announcement of the larger financial support amount, it is difficult to conclude that those are due to the expansion of financial support for dine-in restaurants. For example, it is possible that more people were working from home due to the pandemic, thus the demand for food businesses was higher in residential areas. It is thus necessary to construct a control group for the changes in the number of newly approved dine-in restaurants in the treated area to identify the



(a) Number of Newly Approved Restaurants



(b) Number of Restaurants Going Out of Business

Fig. 6 Number of dine-in restaurants entering and exiting the market in FY 2020 compared to the same months in the previous year by category. Note: We calculate the number of newly approved dine-in restaurants

causal effects of the expansion of financial support on restaurant openings/closings.

The basic idea for estimating the effect of the expansion of financial support for restaurants is to compare the changes in the number of newly approved or closing dine-in restaurants with those in the number of other types in the treated areas, that is, a DID approach with the former as the treatment group and the latter as the control group. Since local governments provided significant financial support only for dine-in restaurants, the expansion of financial support may have increased the number of dine-in restaurants but did not affect the number of other types of restaurants in the treated areas. Additionally, shocks such as the increase in new COVID-19 cases or the increase in the demand for food businesses affected the restaurant industry regardless of business type. The DID approach controls for shocks and identifies the effects of the expansion of financial support for dine-in restaurants.[29]

One could argue that the shocks act heterogeneously by restaurant type. For example, the increase in demand for food businesses in residential areas may encourage entrepreneurs to open new takeout restaurants rather than dine-in ones because the latter may cost more to run. We add a cross-term between the one-period lagged term of new COVID-19 cases in the analyzed prefectures and a restaurant-type dummy to control for the heterogeneous response to shocks.[30] In addition to other types of restaurants in the areas with a declaration of a state of emergency, we use the number of restaurants (both dine-in and other types) in the area where there was no financial support during the sample period (Shizuoka, Hamamatsu, and Okayama) as the control group for the analysis on restaurant openings.[31][32]

The estimation equation is as follows:

$$
\begin{aligned}
y_{mit} = &\beta_0 + \beta_1 T_{mi} + \beta_2 After_t \\
&+ \beta_3 After_t \times T_{mi} + x'_{mit}\gamma_1 + \eta_t \\
&+ \phi_{mi} + u_{mit},
\end{aligned} \tag{1}
$$

where m, i, and t are indices of the municipality, restaurant type (dine-in/other types), and time on a monthly basis, respectively. Dependent variable y_{mit} represents the number of type i restaurants newly approved or closing in municipality m at time t. Variable T_{mi} is a treatment status dummy that takes one for a dine-in restaurant in prefectures with financial support for reducing business hours, and $After_t$ is a dummy taking one for December 2020 or later. The cross-term of T_{mi} and $After_t$ is the DID term. Vector x_{mit} is a set of control variables that includes the one-period lagged term of the prefectural number of positive cases of COVID-19 and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables (e.g., January and February dummies), and the cross-term of quarter (the first, second, third, and fourth quarter dummies) and prefecture fixed effects. The cross-term of the one-period lagged term of the prefectural number of positive cases of COVID-19 and the restaurant type dummy is used to capture the heterogeneous shock by restaurant type discussed above.[33] Parameters η_t and

[29] With the introduction of financial support, people who had planned to open takeout or delivery restaurants might have switched to dine-in restaurants to obtain the support. In this case, the control group would decrease and the treatment group would increase, leading to an upward bias in the estimation. Is such a manipulation feasible? To convert a takeout or delivery restaurant to a dine-in restaurant, they needed to obtain a new license. However, the regulations are stricter for dine-in restaurants than those for takeout or delivery restaurants. For example, a particular issue is the layout of restrooms. Dine-in restaurants must provide restrooms for customers. While restrooms can be shared with employees, they must be located so that customers do not walk through the kitchen to access them. Further, in some municipalities, hand-washing facilities are required. Additional investment will likely be required to accommodate the restroom, but the cost will likely exceed the financial support. Thus, it is difficult to consider such upward bias.

[30] We construct the variable using data from Toyo Keizai Online "Coronavirus Disease (COVID-19) Situation Report in Japan."

[31] One could argue that the demand conditions for the areas where there was no financial support during the sample period (the control area) are completely different from those of the areas where there was financial support (the treated area), biasing estimates. To examine this possibility, we analyze the difference in population and population composition between the treated and control areas. According to the analysis, although there is a difference in population size between the treated and control areas, population density and population composition are similar in both areas. Therefore, demand conditions are not completely different between the two areas. Appendix B.1 discusses the analysis results. In addition, our DID estimate of restaurant openings is robust, even when we exclude the areas without a second declaration of a state of emergency.

[32] In the main estimation, we pooled the two sets of the group into the control group. We implemented a robustness check against the selection of control groups and found that the result is robust.
In addition, we implement a difference-in-differences-in-differences (DDD) model using the above two dimensions of treatment status, the type of restaurant (dine-in or other types of restaurants) and the region (the areas with and without the declaration of a state of emergency). The result of the DDD estimation is comparable to that of the DID estimation. Table 13 summarizes the estimation result of the DDD estimation.

[33] One could argue that it is important to control not only the prefecture-level but also the municipality-level of COVID-19 infections. To examine this possibility, we re-estimate the event study model by adding the municipality-level number of COVID-19 positive cases to the estimation model; adding the municipality-level number of COVID-19 positive cases does not change the estimation results (Fig. 14). Shun-ichiro Bessho and Yusuke Hoshiai at the University of Tokyo provided us data on the municipality-level number of COVID-19 positive cases. We obtained data on the municipality-level number of COVID-19 positive cases from the Real-time Local Information Provider

ϕ_{mi} are monthly and municipality-restaurant-type fixed effects, respectively, and u_{mit} is the error term. The municipality-level restaurant-type fixed effects are controlled by fixed effects estimation with panel data. In Eq. (1), parameter β_3 corresponds to the DID estimate and is the parameter of interest in capturing the effects of the expansion of financial support if the assumption holds.

An assumption for the internal validity of the DID is the common trend assumption; that is, a counterfactual change in the number of newly approved or closing restaurants in the treatment and control groups must have been the same after December 2020 under no expansion of financial support. A typical mean of testing for the validity of this assumption is to check the trends in target outcomes for the treatment and control groups before the policy intervention. If the changes in the number of newly approved restaurants were the same for both groups before the expansion of financial support for dine-in restaurants, the assumption could be maintained. We employ an event study approach to identify the trends in the target outcomes for the treatment and control groups before the expansion of financial support using the following estimation equation:

$$\begin{aligned} y_{mit} = \alpha_0 &+ \sum_{k=Apr2019}^{Oct2020} [\delta_k T_{mi} \times 1\{t=k\}] \\ &+ \sum_{k=Dec2020}^{Mar2021} [\delta_k T_{mi} \times 1\{t=k\}] \\ &+ x'_{mit}\gamma_2 + \tilde{\eta}_t + \tilde{\phi}_{mi} + \epsilon_{mit}, \end{aligned} \tag{2}$$

where variable $1\{t = k\}$ is a dummy taking one if an observation is from the kth month. As we set November 2020 as the reference month, parameter δ_k corresponds to the difference in the number of newly approved or closing restaurants between the treatment and control groups in the kth time period compared to the reference time period. If the estimates of δ_k before December 2020 are statistically indifferent from zero, we can argue that the common trend assumption holds. We utilize the same control variables as in Eq. (1), except for the cross-term of the treatment status dummy and month dummy variables. Parameters $\tilde{\eta}_t$ and $\tilde{\phi}_{mi}$ are monthly and municipality-restaurant-type fixed effects, respectively, and ϵ_{mit} is the error term. We also estimate the equations for restaurant closings.

5 Results

5.1 Effects on entry

The estimation result of the event study supports the common trend assumption. Figure 7 shows the estimated coefficient of the cross-term of the treatment dummy and the monthly dummy variables and its 95% confidence intervals for Eq. (2). The diamond symbols indicate the estimated coefficients of the cross-term of the treatment dummy and monthly dummy variables, and the bars are the 95% confidence intervals for the estimates.

According to Fig. 7, for almost all months, the estimates of δ_k are statistically indifferent from zero at the 5% level before the expansion of financial support, suggesting the credibility of common trend assumption in our setting. In other words, policies other than the expansion of financial support after December 2020 for dine-in restaurants, such as the financial support for restaurants reducing their business hours between April and May and the Go to Eat campaign, do not seem to promote new entries into the restaurant industry. Besides, the estimated coefficients for December 2020 or later are positive and statistically significant at the 5% level, and the differences in the number of newly approved restaurants between the treatment and control groups are 5.2–15.5 restaurants more than that in the reference month.

Note that, as the treatment and control groups of the event study are used for the analysis of the effects of the expansion after December 2020, both groups may include non-representative municipalities. For instance, for the financial support for dine-in restaurants between April and May, the municipalities in the treatment group other than those belonging to Tokyo, Kanagawa Prefecture, and Osaka Prefecture did not provide financial support, which may induce attenuation bias for the estimates for April and May 2020. Additionally, the Go to Eat campaign was held in Shizuoka, Hamamatsu, and Okayama, which are used as the control group in Fig. 7 and may induce attenuation biases for the estimates for November 2020. For these concerns, we re-estimate the event study by

administrated by Tokai University too (https://creativecommons.org/licenses/by/4.0/deed.ja).

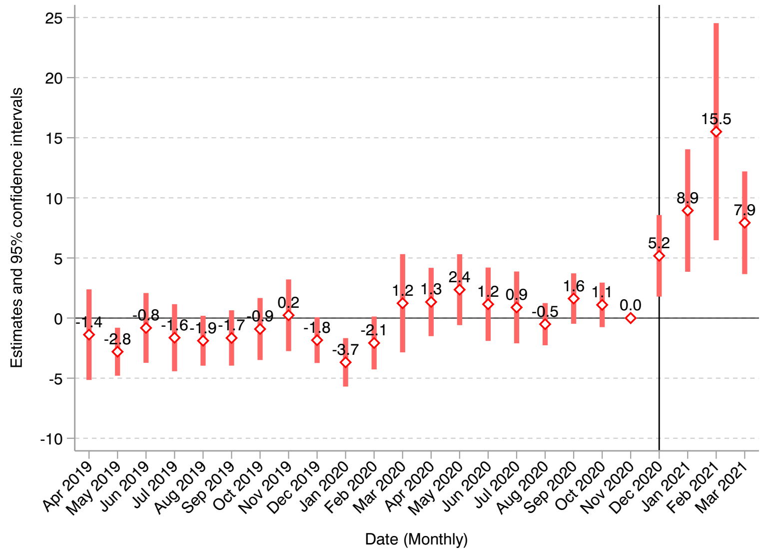


Fig. 7 Event study: restaurant openings. Notes: The diamond symbols indicate the estimated coefficients on the cross-term of the treatment dummy and monthly dummy variables and the bars are the 95% confidence intervals for the estimates. We set November 2020 as the reference month. The confidence intervals are calculated using standard errors robust against municipality-level clustering

excluding the inappropriate municipalities in each case and obtain robust results (Figs. 12 and 13).

We added prefecture monthly fixed effects to the estimation models to control for the unobserved prefecture monthly characteristics such as other industry support policies implemented by prefectures and the COVID-19 cases in neighboring prefectures, which could affect both the expansion of financial support and restaurant entries and exits; we found that adding prefecture monthly fixed effects does not affect the estimation results.[34]

Table 5 summarizes the estimation results of the effect of the expansion of financial support on restaurant openings using the DID approach. The columns show the estimated coefficient on the DID term ("Treated×After"), number of observations, average dependent variable for the treated group before the expansion of financial support ("Pre-expansion mean among treated"), magnitude of the DID estimates evaluated by the percentage change from the pre-expansion average for the treated group, and number of municipalities used for estimation. For the entire sample, the coefficient on the DID term is estimated at 4.566, which is statistically significant at the 1% level. The magnitude of the estimate can be interpreted so that, compared to the average value for the treatment group before the expansion, the number of newly approved restaurants increased by 31.4% among the treatment group after the expansion of financial support. This result suggests that the expansion of financial support for restaurants reducing their business hours prompted more restaurant openings.

The magnitude of the estimated effect is robust when we exclude small municipalities, such as towns (machi/cho) and villages (mura/son), from the analysis (column 2). Among small municipalities, the number of newly approved restaurants is low, with many zero values both before and after the expansion of support, which means a lower variation in the dependent variable resulting in noise. The coefficient on the DID term is 6.08, which is statistically significant at the 1% level. The magnitude can be interpreted in that the expansion of the financial support increased the number of newly approved restaurants by 30.0% among the treatment group compared to the average value before the expansion, which is as high as the magnitude for the entire sample.

We conduct a robustness check against the definition of the control group. One could still doubt that an entrepreneur who plans to open a new takeout restaurant may switch to opening a dine-in one by providing seating to obtain financial support; however, this change is likely difficult as explained in Footnote 29. In this case, the number of newly approved takeout restaurants decreases after the expansion of financial support and the estimated effect of the expansion for dine-in restaurants could be overestimated. The estimation results are robust when we change the control

[34] Table 16 reports the estimation results without and with fixed effects.

Table 5 Effects of the expansion of financial support on restaurant openings

	(1) Whole	(2) Cities/wards	Robustness check against control groups: only using following as control groups (3) Other types of restaurants	(4) Areas without the declaration
Treated × After	4.566***	6.087***	3.773***	4.799***
	(1.057)	(1.424)	(1.133)	(2.367)
Number of observations	3936	2784	3792	2040
Pre-expansion mean among treated	14.549	20.602	14.549	14.549
Magnitude in percentage change (%)				
(compared to the pre-expansion mean)	31.38	29.55	25.93	32.99
Number of municipalities	82	58	79	82

The dependent variable is the number of newly approved restaurants. Standard errors robust against municipality-level clustering are shown between parentheses. All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of positive cases of COVID-19 and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-restaurant type fixed effects, and monthly fixed effects. Inference: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

groups to other types of restaurants in areas with expansion (column 3) and to both types of restaurants in areas without expansion, such as Shizuoka, Hamamatsu, and Okayama (column 4). In addition, we implemented a difference-in-differences-in-differences (DDD) estimation using the two dimensions of treatment status: the type of restaurant (dine-in or other types of restaurants) and the region (the areas with and without the declaration of state of emergency). We found that the DDD estimate is positive and statistically significant, similar to the DID estimation, and its magnitude is comparable to that of the DID estimate (Table 13).

To further explore the impacts of the expanded financial support on the number of new entrants, we analyze the heterogeneous effects between dine-in restaurants operating mainly during nighttime and other dine-in restaurants. To qualify for financial support, dine-in restaurants were required to close by 8 p.m. Considering that most nighttime-oriented dine-in restaurants typically opened at 5 p.m. during non-pandemic times (Fig. 21), they had only a few hours to operate their businesses and receive financial assistance. Consequently, some of these restaurants might have opted to not open altogether instead of reducing their business hours. As such, if a dine-in restaurant specializing in nighttime operations entered the market after the expansion of financial support, they could have been seeking profit through the financial support rather than providing goods and services to customers. To explore this possibility, we separately counted dine-in restaurants based on their type (nighttime-oriented and others) and re-estimated the impacts of the expanded financial support on entries for both categories,[35]

Table 6 summarizes the estimation results of the impact of the expansion of financial support by type of dine-in restaurants (nighttime-oriented and others). The units of observation are the municipality, restaurant type (nighttime-oriented dine-in restaurants, other dine-in restaurants, and other types of restaurants), and the time period. We report the coefficients of the DID term ($Treated \times After$), the cross-term of the nighttime-oriented dine-in restaurant dummy and after dummy ($Nighttime \times After$), and the cross-term of the DID term and the nighttime dummy ($Nighttime \times Treated \times After$).[36] The average num-

35 For some municipalities, we had detailed information on the types of restaurants (Table 2). Using this information, we defined dine-in restaurants such as *izakaya* bars, hostess clubs ("snack" and "cabaret"), and beer gardens as nighttime-oriented dine-in restaurants.

36 If the estimate of the cross-term of the DID term and the nighttime dummy is statistically significant, it suggests a different impact of financial support between nighttime-oriented dine-in restaurants and other dine-in restaurants.

Table 6 Heterogeneous effects between dine-in restaurants that operate mainly during nighttime and other dine-in restaurants (entry)

	(1)
Treated × After	1.784***
	(0.481)
Nighttime × After	−0.239
	(1.662)
Nighttime × Treated × After	0.257
	(1.680)
Number of observations	5328
Pre-expansion mean among treated	
Dine-in restaurants that operate mainly during nighttime	2.596
Other dine-in restaurants	7.850
Magnitude of treated × After in percentage change (%)	
(compared to the pre-expansion mean)	
Dine-in restaurants that operate mainly during nighttime	68.7
Other dine-in restaurants	22.7
Number of municipalities	74

The dependent variable is the number of newly approved restaurants. Standard errors robust against municipality-level clustering are shown between parentheses. All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of positive COVID-19 cases and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-restaurant type (dine-in and other restaurants) fixed effects, and monthly fixed effects. We also controlled for the logged daytime population and logged nighttime population. Inferences: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ber of newly approved dine-in restaurants among the treatment group in the pre-expansion period was 2.596 for nighttime-oriented dine-in restaurants and 7.850 for other dine-in restaurants. According to Table 6, the DID estimate is positive, statistically significant (1.784), and consistent with that in Table 5. The coefficient on the cross-term of the DID term and nighttime dummy is positive but statistically insignificant, suggesting that the expansion of financial support increased the new entrants by 1.784 for both nighttime-oriented and other dine-in restaurants. Compared to the pre-expansion average number of entrants, we can interpret that the support expansion increased the nighttime-oriented dine-in restaurants by 68.7% (=1.784/2.596) and other dine-in restaurants by 22.7% (=1.784/7.850), suggesting a higher impact for nighttime-oriented dine-in restaurants.

Moreover, we conduct a subsample analysis using municipality characteristics to examine the heterogeneity of the impacts based on variables related to the benefits and costs of new restaurant openings. We use two variables for the subsample analysis: population density as of October 2020 and average total rent for vacant restaurants in 2020. The former is a proxy for expected sales because the larger the population is, the higher the demand for food services. The latter is used as a proxy for the opening costs and operating costs of new restaurants. We expect that the effect is larger in areas with high population density and/or with relatively low rent.

Table 7 summarizes the results of the heterogeneous effects analysis. We restrict the sample to municipalities with the expansion of the financial support and divide it by the median of each variable. Appendix A.2 explains the data on population density and total rent. Columns 1 and 2 show the results for the municipalities with below and above median population density, respectively. The results for sub-samples by total rent are shown in columns 3 and 4. The data on total rent are available for 54 municipalities. For the subsample anal-

Table 7 Heterogeneous effects by municipality characteristics

	Population density		Total rent	
	(1) $\leq$ median	(2) $>$ median	(3) $\leq$ median	(4) $>$ median
Treated × After	1.418	6.896	5.367	5.559
	(0.065)	(0.000)	(0.003)	(0.015)
	[−0.0667, 3.017]	[2.615, 11.27]	[1.454, 9.480]	[0.646, 10.93]
Number of observations	1920	1872	1296	1296
Pre-expansion mean among treated	5.933	23.386	13.578	25.076
Magnitude in percentage change (%)				
(compared to the pre-expansion mean)	23.90	29.49	39.53	22.17
Number of municipalities	40	39	27	27

The dependent variable is the number of newly approved restaurants. The wild bootstrap cluster p-values and the wild bootstrap cluster 95% confidence intervals are shown between parentheses and square brackets, respectively, and are calculated using user-written Stata command "boottest" (Roodman et al., 2019). All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of COVID-19 positive cases and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-level restaurant type fixed effects, and monthly fixed effects. Inferences: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ysis, the number of municipalities is below 50, which may lead to problems due to the few clusters used to calculate the cluster-robust standard errors, as discussed by Cameron & Miller (2015). We apply wild cluster bootstrapping with 10,000 replications to tackle the "few clusters" problem using user-written Stata command "boottest" constructed by Roodman et al. (2019). The wild bootstrap cluster p-values and 95% confidence intervals are reported in parentheses and square brackets, respectively.

According to columns 1 and 2 of Table 7, the difference in population density does not significantly affect the magnitude of the effect. The DID estimates are positive, with p-values of 0.065 and 0.000 for areas whose population density is below and above the median, respectively. The estimates imply that, compared to the average value for the treatment group before the support expansion, the numbers of newly approved restaurants increased by 23.9% and 29.5% for below and above the median, respectively. The estimate for the values above the median is around 1.2 times larger than that below the median, implying they do not differ significantly.

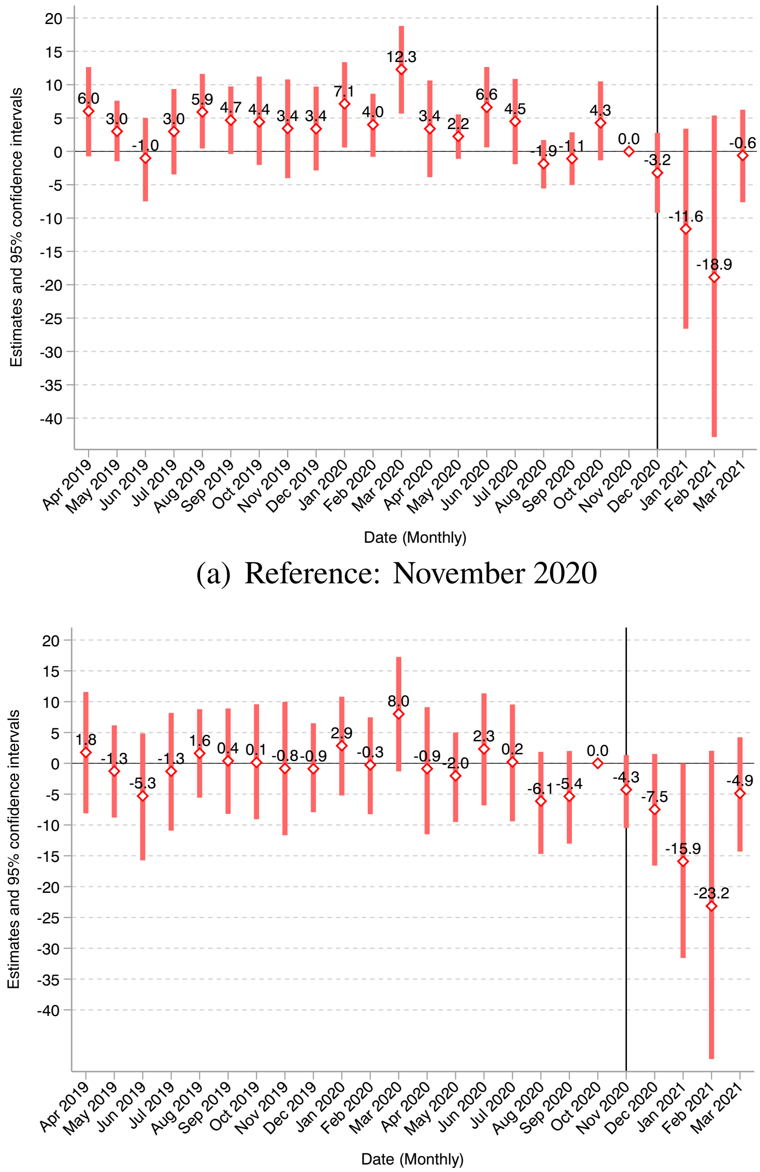
However, the effect is larger in areas where the total rent for vacant restaurants is relatively lower. The DID estimates are positive, with p-values below 0.05. This implies that, compared to the average value for the treatment group before the expansion, the numbers of newly approved restaurants increased by 39.5% and 22.2% for below and above the median, respectively (columns 3 and 4). The estimated effect for the areas whose total rent for vacant restaurants is below the median is around 1.8 times larger than that for those above the median.[37]

5.2 Effects on exit

We conducted the same estimation for restaurant closings using the number of other types of restaurants in the treated areas as the control group. For this analysis, we use two reference months, November 2020 and October 2020. The former is in the same as in Fig. 7, and the latter is used to account for the potential effects of the Go To Eat campaign. As discussed, Fig. 6b shows that the number of restaurant closings in November 2020 was lower compared to the same month of 2019.

[37] One could argue that the low-rent areas coincide with residential areas, where the demand for dine-in restaurants increased during the pandemic due to changes in working habits. If this is the case, it is difficult to interpret the results from the subsample analysis of the total rent for vacant restaurants as the difference in the cost of restaurant openings. We analyzed the relationship between total rent and daytime and nighttime population densities, which are proxies for demand-side factors, to examine the above possibility. We did not find any statistically significant difference in population densities between the high and low total rent areas (Table 11), showing that total rent does not necessarily coincide with demand factors.

Fig. 8 Event study: restaurant closings. Notes: The diamond symbols indicate the estimated coefficients on the cross-term of the treatment dummy and the monthly dummy variables, and the bars are the wild bootstrap clusters of 95% confidence intervals robust against municipality-level clustering calculated using user-written Stata command "boottest"(Roodman et al., 2019). We set November 2020 and October 2020 as the reference months for **a** and **b**, respectively



(a) Reference: November 2020

(b) Reference: October 2020

From the result of the descriptive analysis, we cannot deny the possibility that the Go To Eat campaign prevented restaurant closings.[38] The campaign aimed to encourage people to eat at dine-in restaurants, while the restaurants could get the subsidy for operating businesses. As such, the campaign might have prevented the restaurants that wanted to continue business from closing but not restaurant openings for the subsidy. Therefore, we used the reference month of October 2020 for the analysis of restaurant closings.

When we use the reference month of November 2020, approximately 80% of the estimates of δ_k for the pre-expansion period are statistically indifferent from zero at the 5% level, while we obtain four statistically significantly positive estimates for the period (Fig. 8a). The four positive estimates may indicate that the Go To Eat campaign held in November 2020 prevented

[38] The estimation results suggest that the campaign had a limited impact in promoting entries in the restaurant industry (Figs. 6b and 13).

restaurants from closing. Subsequently, the result suggests a large reduction in restaurant closings among the treated group in January and February 2021, but the estimates are marginally insignificant at the 10% level (p-values were 0.117 and 0.114 for January and February, respectively).

When we change the reference month from November to October 2020, the tendency of the results does not change significantly. All estimates of δ_k for the pre-expansion period are statistically indifferent from zero at the 5% level (Fig. 8b). For November 2020, the estimate of δ_k is negative but not statistically significant for the above expectation. The negative estimate might indicate the possibility that the Go To Eat campaign prevented restaurant closings; however, our event study model suggests that, at least on average, the treated and control groups were statistically the same in November 2020 compared to October 2020. Then, the result suggests a statistically significant reduction in restaurant closings among the treated group in January and February 2021 at the 5% and 10% levels, respectively.[39] The magnitudes are −15.9 and −23.2 for January and February, respectively. In this setting, we obtained a large reduction in restaurant closings among the treated in December 2020, but the estimate is not statistically significant (p-value = 0.120). If we use October 2020 as the reference month, we obtain statistically significant estimates for the post-expansion period, while the tendency of the estimates is the same as when November 2020 was the reference month. From the following DID analysis, we utilized the same after dummy as in the analysis on restaurant openings.

Table 8 summarizes the results of the DID analysis on restaurant closings. We applied wild cluster bootstrapping in the same manner as in Table 7 because the number of clusters is 39. The wild bootstrap cluster p-values and 95% confidence intervals are reported in parentheses and square brackets, respectively.

According to column 1, the coefficient on the DID term is −5.028, with a p-value of 0.079. The magnitude of the estimate can be interpreted in that, compared to the average value for the treatment group before the expansion, the number of restaurants that went out of business decreased by 30.0% after the support expansion. The results suggest that the expansion of financial support for restaurants reducing their business hours prevented restaurants from going out of business.

[39] The p-value for the estimate for February 2021 is 0.068.

5.3 Heterogeneous effects on entrants and exiters

This section examines how the expansion of financial support affects entrants and exiters differently based on their characteristics. We conducted a restaurant-level DID estimation using dummies indicating whether an entrant was a chain restaurant,[40] whether a new dine-in restaurant applied for both dine-in and takeout services,[41][42] whether a new dine-in restaurant had already possessed licenses for takeout services,[43] whether an exiter is a chain restaurant, the logged duration of operation for an exiter, and a dummy variable indicating the duration of operation for an exiter was below 1 year as dependent variables.

Table 9 summarizes the results of the restaurant-level analysis.[44] We applied wild cluster bootstrapping in the same manner as in Table 7 for columns 4–6 because the number of clusters is 35–38. The wild bootstrap cluster p-values and 95% confidence intervals are reported in parentheses and square brackets, respectively.

We obtained statistically significant DID estimates for the dummy indicating that entrants applied for both dine-in and takeout services and the dummy indicating if the duration of operation for an exiter was below 1 year (columns 2 and 6). The DID estimate for the double-application dummy is negative (−0.005) and

[40] We constructed the chain restaurant dummy using the names of restaurants and the list of major chain restaurants published by a private company, NSS Corporation. NSS Corporation sells a list of chain restaurants and publishes reports on the annual rankings of the number of locations for chain restaurants (https://www.nipponsoft.co.jp/blog/analysis/)(only in Japanese)(accessed on August 1, 2023).

[41] In some municipalities, we did not have access to detailed information on the types of restaurants and classified restaurant types using the names of restaurants. We excluded those municipalities for accuracy.

[42] We used Shizuoka City, Hamamatsu City, and Okayama City as a control group.

[43] The dummy variable was created based on the lists of newly approved restaurants since FY2018. Saitama City and Kawagoe City were excluded from the variable construction due to data availability from FY2019 only. We identified identical restaurants by matching their names and addresses. We compiled the license application history for each restaurant; the dummy variable takes a value of one if a new dine-in restaurant with multiple license applications since FY2018 had obtained a takeout services license in the preceding application.

[44] We excluded Toshima Ward, which provided data in hard-copy format for accuracy.

Table 8 Effects of the expansion of financial support on restaurant closings

	(1)
Treated × After	−5.028
	(0.079)
	[−10.55, 0.566]
Number of observations	1872
Pre-expansion mean among treated	16.747
Magnitude in percentage change (%)	
(compared to the pre-expansion mean)	−30.02
Number of municipalities	39

The dependent variable is the number of restaurants that have gone out of business. The wild bootstrap cluster p-values and 95% confidence intervals are shown between parentheses and square brackets, respectively, and are calculated using user-written Stata command "boottest"(Roodman et al., 2019). All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of positive COVID-19 cases and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-restaurant type fixed effects, and monthly fixed effects

Table 9 Effects on the characteristics of entrants and exiters

	Entry			Exit		
	(1) Chain restaurant	(2) Apply both dine-in/takeout	(3) Possessed licenses for takeout	(4) Chain restaurant	(5) Logged duration	(6) Duration $\leq$ 1 year
Treated × After	0.020	-0.005**	−0.003	−0.011	0.209	−0.115
	(0.019)	(0.003)	(0.005)			
				⟨0.851⟩	⟨0.348⟩	⟨0.058⟩
				[−0.184, 0.107]	[−0.297, 0.830]	[−0.256, 0.016]
Number of observations	41,427	22,381	27,846	22,093	15,735	15,807
Pre-expansion mean among the treated	0.030	0.020	0.003	0.030	1667.230	0.140
Number of municipalities	81	76	79	38	35	35

The unit of observation is the number of restaurants that entered and exited the market. The dependent variables include dummies indicating whether an entrant is a chain restaurant, whether an entrant applied for both dine-in and takeout services, whether an exiter is a chain restaurant, the logged duration of operation for an exiter, and a dummy variable indicating if the duration of operation for an exiter was below 1 year. In columns 1–2, standard errors robust against municipality-level clustering are shown between parentheses. In columns 3–5, the wild bootstrap cluster p-values and 95% confidence intervals are shown between parentheses and square brackets, respectively, and are calculated using user-written Stata command "boottest" (Roodman et al., 2019). All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of positive COVID-19 cases and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-restaurant type (dine-in and other restaurants) fixed effects, and monthly fixed effects. Inferences for Columns (1)-(3): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

statistically significant at the 5% level. This can be interpreted as the expansion of the financial supports leading to a 25% decrease in double-application among entrants compared to the pre-expansion mean among the treatment group. As discussed in Footnote 29, one could argue that, with the introduction of financial support, people who had initially planned to open takeout or delivery restaurants might have switched to dine-in restaurants to obtain financial support. In this case, they may apply for both dine-in and takeout services, but the DID estimate indicating the decrease in double applications does not support this possibility. This could be because applying for dine-in services requires more facilities and additional investment, which could reduce the benefit from the financial support.

The DID term for the dummy indicating if the duration of operation for an exiter was below 1 year is negative and statistically significant, with a p-value of 0.058. The results imply that the financial support expansion decreased the number of restaurants that exited in the short run compared to the mean of the treatment group before the expansion by 82% among exiters. Previous studies show that firms that are unproductive and less innovative tend to exit the market quickly (e.g., Aga & Francis, 2017; Jovanovic, 1982; Kato et al., 2022; Melitz, 2003; Muzi et al., 2023). This suggests that the restaurants that exited within 1 year could be relatively less productive. The DID estimate suggests that the expansion of financial support could enable low-productivity restaurants to remain in the market. For other dependent variables, we did not observe any statistically significant impacts of the expansion of financial support.

6 Discussion

6.1 Who enters the market after the expansion of financial support?

The estimation results suggest that the expansion of financial support for dine-in restaurants induced an increase in the number of new entrants. The support amount could be substantial after the expansion, given that it exceeded the sales of most dine-in restaurants during the pre-pandemic period when its daily value was JPY 60,000.[45] However, due to the sharp decline in eating-out expenses caused by the pandemic (Fig. 2) and the government-imposed restrictions, restaurants faced a challenging business environment. The expansion of financial support increased the expected revenue for dine-in restaurants, which could give various people an incentive to open new dine-in restaurants.

There are three possible types of new restaurant entries: (1) "truly" new dine-in restaurants, (2) incumbent restaurants with licenses for takeout and delivery services that obtained an additional license to operate as dine-in restaurants, and (3) people who had initially planned to open takeout or delivery restaurants obtained licenses for both dine-in and takeout services.

The first possibility means a restaurant newly opened as a dine-in service in response to the expanded financial support. In this case, we should also consider the cost of operating dine-in restaurants. The high operating costs may cancel out the increase in expected revenue and the incentive to open such restaurants. The rent for restaurants, one component of the fixed cost, differed,[46] but the amount of financial support was the same across municipalities in each prefecture between December 2020 and March 2021.[47] The extent of the incentive induced by the expanded financial support could vary across areas: lower operating costs could lead to higher incentives for opening new dine-in restaurants. The estimation results showing the larger magnitude of the increase in the number of new dine-in restaurants among the areas with lower rent (columns 3 versus 4 in Table 7) support this possibility.

The results also indicate a greater increase in the number of new dine-in restaurants that appear to have been launched with relatively lower opening costs. If entrepreneurs open a dine-in restaurant with the intention of suspending operations immediately, opening

[45] In the pre-pandemic period, around 75.4% of dine-in restaurants had monthly sales below JPY 1.8 million. Please see Appendix B.4.

[46] The rent per square meter ranges between JPY 2180 and JPY 10,250 in Tokyo and between JPY 2160 and JPY 8540 in Kanagawa Prefecture (panels B and C of Table 10).

[47] Tokyo metropolitan government set the same amount of financial support for all municipalities. There was a difference in the timing of the introduction of financial support across municipalities in Kanagawa Prefecture, but the amount of support was constant for all municipalities.

costs can be reduced. The proportion of dine-in restaurants with opening costs below the financial support for one month is 12.2% when restaurants open but take an immediate break and 4.4% when restaurants open as usual (panel A of Table 18).[48] The proportion of dine-in restaurants with opening costs below the financial support amount for two months and three months are 29.2 and 43.9%, respectively.[49] Actually, the estimation results show that the impact of the expanded financial support on entry is larger among nighttime-oriented dine-in restaurants (Table 6), which could have been considered a break instead of a business hour reduction. Furthermore, if a vacant restaurant is equipped with the necessary facilities for another restaurant service, opening costs can also be reduced. If restaurants inherit land, stores, and equipment from other firms and open but take an immediate break, the proportion of dine-in restaurants with opening costs below the financial support amount for one month is 32.0% (panel A of column 4 in Table 18). For two months, the proportion increases to 48.0%, and for three months, it further rises to 64.0% (panels B and C in column 4 of Table 18). Immediately after the expansion of the financial support was announced, the proportion of dine-in restaurants that began operations in locations where other restaurants had been previously approved increased more than twice compared to the same period in the previous year in areas with low total rent for vacant restaurants (Fig. 15). This implies that some entrepreneurs utilized vacant restaurants with the necessary facilities to reduce the cost of opening a new dine-in restaurant in time to apply for financial support.[50]

The second possibility for the new dine-in restaurants is that incumbent restaurants with licenses for takeout and/or delivery services obtained additional licenses for dine-in operations to become eligible for financial support. If this was the case, the number of new dine-in restaurants that had already licenses for takeout services could have increased after the expansion of financial support. However, our results do not support the increase in the number of those new dine-in restaurants (column 3 of Table 9). Additionally, individuals who had initially planned to open takeout or delivery restaurants may have applied for both dine-in and takeout services (the third possibility). However, the estimation results do not support this possibility (column 2 of Table 9). As discussed in Footnote 29, obtaining licenses for dine-in services requires more facilities and additional investment compared to obtaining licenses for takeout and/or delivery restaurants. This could potentially reduce the benefits gained from the financial support, leading to the scenario where incumbents may not have acquired additional licenses for dine-in restaurant operations.

The COVID-19 pandemic has had a significant impact on the demand for eating out. According to Fig. 2, the demand for dining out decreased substantially after March 2020, and it took 3 years for it to return to pre-pandemic levels. However, despite this trend, our data show a notable increase in the number of new dine-in restaurants during the early stages of the pandemic. Additionally, these new restaurants had relatively low opening and operation costs. For instance, when a vacant restaurant was used for opening a new restaurant, it might indicate a lack of potential customers or other problems in the area, making it difficult to generate market revenue. Furthermore, our data show an increase in the number of newly approved dine-in

[48] We calculated the proportions using data from the pre-pandemic period. We assumed the financial support amount for one month to be JPY 1.8 million (JPY 60,000 times 30 days). Appendix B.4 discusses this issue in more detail.

[49] We assume that the financial support amount for two months is JPY 3.6 million (JPY 60,000 times 60 days) and for three months JPY 5.4 million (JPY 60,000 times 90 days).

[50] Moreover, one could argue that entrepreneurs may have anticipated the discontinuation of financial support in the short term. If this is the case, opening new restaurants seems very risky. However, it is conceivable that most Japanese did not expect an early end to the pandemic. According to a survey conducted in June 2020, 77.1% of the respondents indicated that they believed the pandemic would persist beyond July 2021 (1 year after the survey was conducted). Additionally, 21.2% of the respondents thought that the pandemic would continue after 2023 (2.5 years after the survey was conducted) (Morikawa, 2020). In December 2020, the number of new COVID-19 cases increased substantially compared to June 2020 (about 50 times more cases), and the preparation for vaccination was delayed in Japan (Kosaka et al., 2021). As a result, it is possible that, as of December 2020, people may have anticipated the pandemic to persist in the long term. In addition, as previously discussed, the prime minister announced that the national government would support local governments to expand the financial support for reducing business hours for dine-in restaurants in December 2020. Therefore, the entrepreneurs might have anticipated continuous requirements to reduce nighttime business hours based on financial support in December 2020. For example, the financial support continued for approximately 11 months after December 2020 in Tokyo and Kanagawa Prefectures.

restaurants that closed within 30 days of approval during the first quarter of 2021 (after the expansion of support) compared to FY2019 (Fig. 16), especially in February and March 2021, despite the decrease in the proportion of exits from young restaurants discussed in Section 5.3.[51] These findings suggest that the new businesses were established mainly to obtain financial aid rather than a long-term vision of providing better goods and services for customers. This confirms the results of previous studies that show reducing entry barriers leads to less profitable and marginal new firms (e.g., Branstetter et al., 2014; De Meza, 2002; Santarelli & Vivarelli, 2002). Although the policy of supporting new restaurant entrants in COVID-19 was a coincidence, it is unlikely to be effective. Considering the importance of supporting new firm entries for maintaining economic growth and securing employment during a recession (Aghion et al., 2009, Audretsch, 2007), alternative policies need to be considered.

6.2 Financial support and market exits

The estimation results show that the increase in financial support led to a decrease in the number of dine-in restaurants closing down. Specifically, among those restaurants that did close, the percentage of those that did so within a year decreased significantly (82%). As previously discussed, because previous studies show that less productive and innovative firms are more likely to exit the market quickly (e.g., Aga & Francis, 2017; Jovanovic, 1982; Kato et al., 2022; Melitz, 2003; Muzi et al., 2023), the restaurants that exited the market within 1 year could have been relatively unproductive. The results suggest that the financial support might have enabled low-productivity restaurants to remain in the market. This result is consistent with previous studies that found government support programs, such as public guarantees on private loans and subsidies during the COVID-19 shock, to support less productive firms that would otherwise have exited the market, thus enabling them to survive (e.g., Belghitar et al., 2022; Block et al., 2022; Dörr et al., 2022; Honda et al., 2023; Hoshi et al., 2023; Morikawa, 2021; Muzi et al., 2023). This weakens the cleansing effects of recessions (recessions typically remove low-productivity firms from the market and encourage high-productivity firms to enter the market) (e.g., Dörr et al., 2022; Muzi et al., 2023).

6.3 Potential impacts on the restaurant industry and policy implications

The results not only suggest the possibility that the expansion of financial support weakened the cleansing effects of the recession, as discussed in previous studies, but also the possibility that the expansion increased the number of entrants focused on obtaining financial support rather than providing better goods and services for customers. As such, the financial support for restaurants during the COVID-19 recession should have included systems to prevent new entrants, especially undesirable entrants.

One possible measure to prevent new entrants is to provide financial support only to incumbent restaurants when business hour reductions are required. For instance, Germany's Corona Bridging Aid for SMEs[52] and other Japanese programs to assist businesses affected by the pandemic[53] supported only those established before the pandemic. The local governments required dine-in restaurants to reduce their nighttime business hours by offering financial support and imposing monetary penalties following the support expansion. To prevent undesirable new entrants, a system that provides financial support and imposes monetary penalties on incumbent restaurants (started a business before the pandemic) could be used, while only imposing penalties on new entrants (started a business during the pandemic before nighttime restrictions were enforced by local governments). One could argue that imposing penalties only on new entrants might inhibit entries onto the restaurant market. However,

[51] There is no contradiction between the two results. We re-estimated column 6 of Table 9 by splitting the post-intervention dummy of the DID model into two separate dummy variables. One takes the value of one for December 2020 and January 2021, and the other takes the value of one for February and March 2021. This re-estimation yielded a statistically significant DID estimate from December 2020 to January 2021.

[52] This program excluded firms incorporated after October 31, 2019. Please refer to FAQ No. 1.1 on the web page (https://www.ueberbrueckungshilfe-unternehmen.de/DE/FAQ/Ubh-I/ueberbrueckungshilfe-i.html?cms_artId=8a62639a-8dd9-4ed0-a837-782c7f894e1a)(in Germany)(accessed on September 6, 2023).

[53] The Business Continuity Grant (*jizokuka kyufukin*) and the Office Rent Grant (*yachin shien kyufukin*) were available for firms that had earned income in 2019 or earlier.

since the program aimed at restricting nighttime business, nighttime-oriented dine-in restaurants might have been restricted, but daytime-oriented dine-in restaurants and takeout/delivery restaurants were unlikely to be restricted. The restriction on new nighttime-oriented dine-in restaurants could align with the government's goal of reducing infection clusters in dine-in restaurants during nighttime.[54]

Another possible measure is to set varying amounts of financial support based on the sales of individual restaurants, even when providing financial support to new entrants. Since the financial support aims to compensate for the reduced sales due to the nighttime business hour reduction, the amount of financial support based on sales is more reasonable than a uniform amount. Local governments revised the amount of financial support for dine-in restaurants that had to reduce their nighttime business hours from a uniform amount to an amount based on individual sales after April 2021. For instance, between April 12, 2021, and March 11, 2022, the Tokyo Metropolitan government set the amount of financial support based on the daily sales in previous years (2019 or 2020) for each incumbent restaurant and based on the daily sales between the opening date and April 11, 2021, for restaurants that had operated within two months.[55] Since the total rent (a component of fixed costs of operating restaurants) differs across the municipalities in a prefecture (panels B and C of Table 10), the uniform amount can increase the incentives for restaurants to enter the market in a certain area. The estimation results support this possibility. The amount of financial support based on the sales of individual restaurants could reduce the fluctuation of the incentive to enter the market due to financial support and prevent undesirable entrants.

7 Conclusions

This study investigates the impact of financial support for the compensation of business hour restrictions during the pandemic on dine-in restaurant entries. Our findings reveal that the expansion of financial support from December 2020 to March 2021 increased the number of dine-in restaurant openings and decreased the number of dine-in restaurant closures. Throughout FY 2020, the number of restaurant openings remained consistent with the pre-pandemic trend on an annual basis, and the number of restaurant closures was even lower than predicted by pre-pandemic data, despite the decreased demand for eating out. This suggests that there were excessive entries in the restaurant industry. The results also indicate that the expansion had a greater impact in areas with lower opening and operating costs, while it did not vary based on the measure anticipating potential sales. In the first quarter, from December 2020 to March 2021, our data present an increase in the number of newly approved dine-in restaurants that closed within 30 days of approval compared to FY2019. This is consistent with previous studies that found universal government support programs lead to an increase in less profitable and marginal firm entries.

During the pandemic, financial support was provided to compensate for the restrictions on dine-in restaurant business hours. However, unlike other support programs, this support was offered to both possible entrants and incumbents. As a result, the expanded financial support not only prevented firm exits but also increased entries. Unfortunately, due to the lack of a system to prevent new, particularly undesirable, entrants, the entrants induced by the financial support cannot be considered desirable for the restaurant market. To address this issue, the financial support should have been expanded with measures to prevent new entries, especially those deemed undesirable. One potential solution could involve restricting applications to only incumbent dine-in restaurants and varying the amount of financial support based on the sales of individual restaurants. This approach was implemented for other programs, and it was applied to the financial support for dine-in restaurants after mid-April 2021.

This study has some limitations. One limitation is the generalizability of our results. As discussed in Section 3, we collected data mainly from the municipalities in the Tokyo metropolitan Area, but large cities in other prefectures also declared a second state of emergency. As such, our results could be used for policymaking in urban areas, but it is challenging to apply them to the entire Japan, including rural areas. An expansion of this

[54] In situations where new entrants could access financial support, we observed a greater increase in nighttime-oriented dine-in restaurants in response to the expansion of financial support (Table 6). This contradicts the program's intended goal of restricting nighttime business.

[55] Please see pages 13 and 14 on the webpage (https://www.sangyo-rodo.metro.tokyo.lg.jp/topics/jitan9.pdf)(in Japanese)(accessed on September 7, 2023) for details.

study to a more generalized population could be the scope of future studies. It is also important to acknowledge the limitations concerning the external validity of our findings for other contexts, different industries, and different countries and regions. The policy impacts of financial support for new firms are contingent upon the unique context that entrepreneurs face within each country and region or within an industry. Therefore, generalizing our results to other contexts should be done with caution. Future research could focus on validating the external validity of our findings by examining the effects of similar policies implemented during recessions in different countries.

Another limitation is that because of data limitations, we did not analyze the long-term impact of financial support on entries. The data are available up to April or May 2021 and do not cover the period after financial support was completely discontinued. Our results suggest that some dine-in restaurants that opened during the expansion of financial support may have ceased their operations due to reduced support amount after April 2021. In other words, there could have been a further decline in the number of these restaurants after support was completely terminated. Under this scenario, the entrants during the period of financial support expansion may have little contribution to the efficiency of the restaurant market. The evaluation of the long-term impacts on the restaurant industry should be a focus of future studies. The productivity of new entrants in response to the expansion of financial support should be examined. The expansion of financial support may induce the entry of low-productive restaurants. Even if such restaurants continue their operations after the discontinuation of financial support, it would not contribute to the efficiency of the restaurant market. This aspect is not addressed in this paper owing to data limitations and could be a subject for future studies.

Appendix

A Additional information on the dataset

A.1 Types of restaurants

Food businesses can be classified as restaurants, coffee shops (kissa-ten), businesses selling foods such as raw and processed ones, and food manufacturers. In the analysis, business entities with licenses for restaurants and coffee shops are the analysis subjects and, hereafter, we call them coffee shop restaurants. Additionally, we can classify restaurants and coffee shops for most municipalities. For instance, according to data from the Tokyo Metropolitan Government, restaurants are classified as restaurants, sushi restaurants, soba noodle restaurants, bars, bento shops, delicatessen, caterers (including pizza delivery store), facilities for mass feeding (including student cafeterias), hotels, and convenience stores. In Japan, convenience stores serve food prepared in the store, and these stores also need business licenses for cooking. We utilize the information on the types of approved businesses to classify restaurants into dine-in restaurants and other types of restaurants, including those serving food only as takeout or as delivery. Since convenience stores were not eligible for financial support, we classify those as other types of restaurants. Using data from the Tokyo Metropolitan Government, a restaurant which has at least one license for one type of restaurant, such as sushi restaurants, soba noodle restaurants, or bars, is classified as a dine-in restaurant. A restaurant without a license for dine-in is classified as other type. For instance, if a restaurant has licenses for restaurant and delicatessen, we classify it as a dine-in restaurants, while if a restaurant only has a caterer license, we classify it as other type. In some municipalities, we do not have access to detailed information on restaurant types. In such cases, we use the name of restaurants to classify them into types. For instance, restaurants not eligible for financial support, for example, major convenience stores, major pizza delivery stores, school cafeterias, and employee cafeterias according to their names, are classified as other types of restaurants. The last column in Table 2 provides detailed information on the types of restaurants.

A.2 Municipality characteristics

We utilize two types of municipality characteristics, population density as of October 2020 and average total rent for vacant restaurants in 2020, to conduct subsample analysis for the heterogeneity of the effect on restaurant openings by the potential benefits and costs to open new restaurants. The former is a proxy for expected revenue because the larger the population is, the greater is the demand for food services, while the latter is used

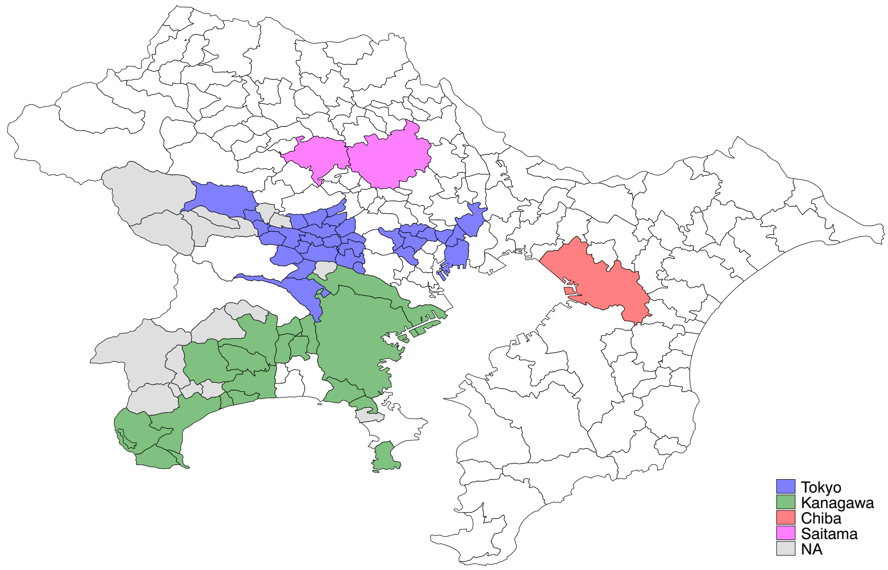


Fig. 9 Municipalities in the Tokyo metropolitan area for which data on total rent of restaurants for 2020 are available. Notes: The data are also available for Sakai

as a proxy of the cost to open new restaurants. The data on population density are available from the 2020 Population Census for all municipalities.[56] Data on the average rent for vacant restaurants in 2020 are available from a website publishing lists of vacant restaurants for renting operated by a private company.[57] The website releases data on the average rent per area per month and average surface area of vacant restaurants for some municipalities, and the average values are calculated based on the vacant restaurants listed on the website. Data for 2018 and 2021 are available for most municipalities. If no vacant restaurant is listed on the website for a municipality in a year, we cannot utilize the data for the municipality in that year. Additionally, for some large municipalities, the data are published by municipality subdivisions and, for each municipality, we define an average value of the variables as the average for the municipality. For instance, the data for Yokohama are published by its 18 subdivisions and the average rent per area of Yokohama is defined as the average value of the average rent per area for all subdivisions. We use the data for 54 municipalities, and Fig. 9 shows municipalities where the data for 2020 are available. Using the average values, we define the average total rent per month for each municipality by multiplying the average rent per area and average surface area.

Table 10 shows summary statistics for population density and the average total rent for municipalities with financial support expansion. The population density ranges from 19.0 to 23,220.45, thus showing variation within the sample municipalities (panel A). The mean of the average total rent per month is around JPY 497,000 (≈ \$4543) (Table 1), and the average total rent per month ranges from JPY 97,000 JPY to 1430,000 (≈ \$887 − \$13071) (panel A).[58] For the subsample analysis, we divide the sample by the median for each variable.

Table 11 summarizes the relationship between total rent and daytime and nighttime population.[59] The first and second columns show the average value of each variable for the municipalities whose total rent is below and above the median, respectively. The third column shows the differences between the first and sec-

[56] The dataset can be downloaded from the official statistics portal of Japan, e-Stat https://www.e-stat.go.jp/api/sample2/tokeidb/getMetaInfo?statsDataId=0003433220. The data include the population in 2015, change in population from 2015 to 2020, and surface area for each municipality. We calculate the population in 2020 by summing the 2015 population and the change and divide it by the surface area to obtain population density.

[57] https://www.inshokuten.com/.

[58] We use the central bank rate of June 11, 2021, of USD/JPN 109.40 to convert JPY to USD. (https://www.boj.or.jp/statistics/market/forex/fxdaily/fxlist/fx210611.pdf)(accessed on June 11, 2021)

[59] The daytime and nighttime population is available in the 2020 Population Census.

Table 10 Summary statistics for rent and population density in 2020

	Mean	SD	Min	p25	p50	p75	Max	Number of municipalities
A. Whole								
Total rent	496.97	290.65	97.00	338.84	445.35	605.61	1429.93	54
Area (square meter)	130.00	128.69	44.99	70.55	89.06	127.24	620.43	54
Rent per square meter	4.50	1.85	2.16	3.09	4.22	5.52	10.25	54
Population density	6015.16	6073.96	19.00	1163.77	4356.47	8946.20	23,220.45	79
B. Tokyo								
Total rent	446.03	191.22	119.03	312.37	402.62	607.02	903.91	31
Area (square meter)	90.52	44.89	49.19	65.52	77.26	89.92	239.11	31
Rent per square meter	5.16	1.87	2.18	3.49	5.11	6.09	10.25	31
Population density	8304.63	6878.12	19.00	1293.07	7454.35	12,201.61	23,220.45	45
C. Kanagawa								
Total rent	600.94	411.74	97.00	338.84	499.99	620.40	1429.93	19
Area (square meter)	197.83	194.36	44.99	96.07	114.05	187.07	620.43	19
Rent per square meter	3.61	1.54	2.16	2.30	3.32	4.23	8.54	19
Population density	2850.46	2900.14	42.64	762.93	1838.28	3802.16	10,762.05	28

The unit for total rent and rent per square meter is JPY 1000

ond columns, and the fourth column the magnitude of the differences by comparing with the average values among the municipalities whose rents are below the median. This table demonstrates that there are no statistically significant differences in the daytime and nighttime population density between the municipalities with high total rent and those with low total rent.

B Additional descriptive statistics and estimation results

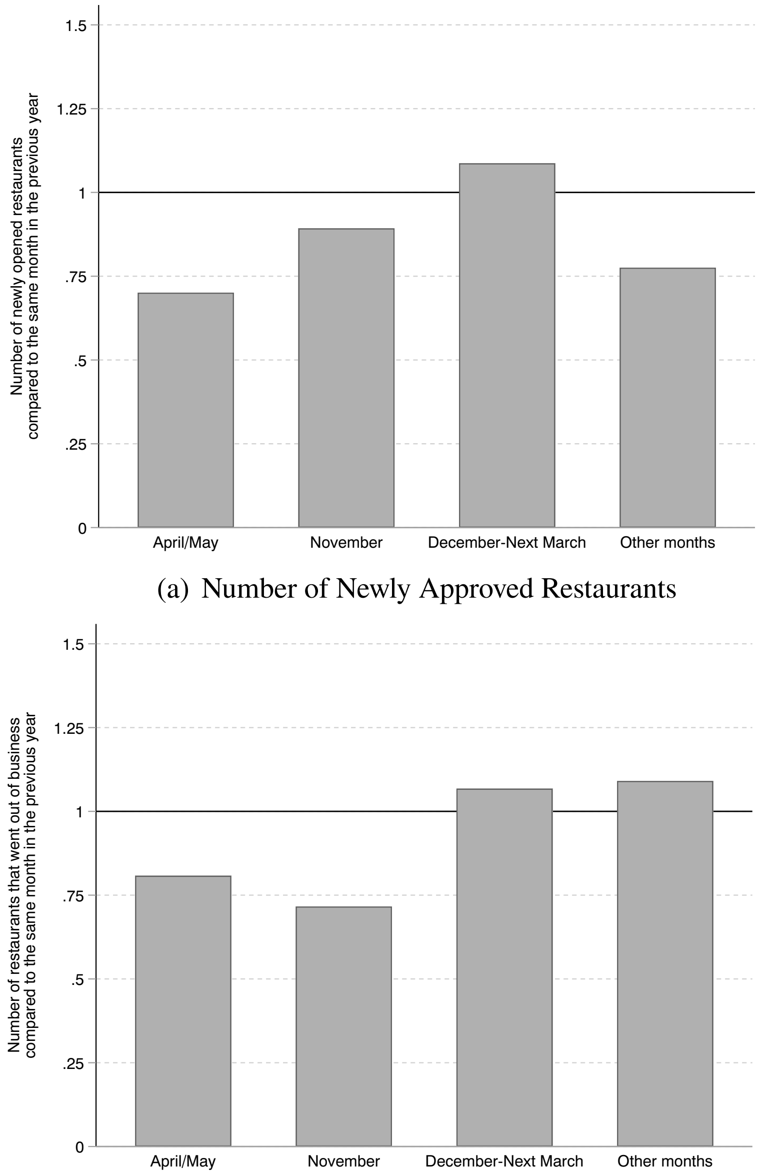
Figure 10 shows the number of newly approved other restaurant types in FY2020 (panel a) and that of other types of restaurants that went out of business (panel b) compared to the same months in the previous year by

Table 11 Relationship between total rent and population

	Total rent		
	(1) $\leq$ median	(2) $>$ median	(3) Difference
Daytime population per square km	8498.3	9827.3	1329.1
			(2592.6)
Nighttime population per square km	8807.4	7832.6	−974.8
			(1645.6)
Daytime population	279,343.7	353,740.3	74,396.6
			(144299.6)
Nighttime population	291,056.0	340,335.3	49,279.3
			(154,644.5)

The first and second columns show the average values of each variable for the municipalities whose total rent is below and above the median, respectively. The third column shows the differences between the first and second columns. For the third and fourth columns, standard errors are between parentheses. Inferences: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Fig. 10 Number of other types of restaurants entering and exiting the market in FY 2020 compared to the same months in the previous year by category. Notes: We calculate the number of newly approved other restaurant types



(a) Number of Newly Approved Restaurants

(b) Number of Restaurants Going Out of Business

category: April and May, November, December to next March, and other months. In FY2020, the first round of financial support for restaurants to reduce their business hours was provided in April and May, the Go-To-Eat campaign was held in November, and the financial supports were expanded from December to the next March. In other months, there were few support programs for dine-in restaurants.

B.1 The difference in demographic characteristics between the treated and the control areas in 2020

Table 12 summarizes the demographic characteristics by area using the 2020 Population Census. The first column shows the demographic characteristics for Shizuoka, Hamamatsu, and Okayama, the control area, and the second column shows the demographic charac-

Table 12 Differences in demographic characteristics between the treated and the control areas in 2020

	(1) Control area	(2) Treated area	(3) Difference
Population	722,380.67	230,437.18	−491,943.49*
			(276,754.54)
Population per square km	625.09	5819.45	5194.36
			(3382.74)
Female ratio	51.30	50.44	-0.86
			(1.37)

The first and second columns show the average value of each variable for the municipalities in the treated area and those in the control area (Shizuoka, Hamamatsu, and Okayama). The third column shows the differences between the first and second columns. For the third and fourth columns, standard errors are between parentheses. Inferences: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

teristics for municipalities in the area where the second state of emergency was declared, the treated area. The control area, on average, has more population than the treated area at the 10% significance level. By contrast, population density is higher in the treated area than in the control area, while it is not statistically significant at the 10% level.

Although there is a difference in population size between the treated and control areas, population density and population composition are similar in both areas. The female ratio in the treated area is comparable to that in the control area (Table 12). The proportion of the population in the age group in the treated area is comparable to that in the control area for most age groups and for both men and women (Fig. 11).

B.2 Robustness checks

Figure 12 presents the results of the re-estimation of the event study by excluding from the sample the municipalities which did not provide financial support for dine-in restaurants reducing their business hours between April and May 2020. The estimation results are robust against area selection and do not support the significant impact of financial support between April and May 2020. Figure 13 summarizes the results of the re-estimation of the event study by excluding from the control group the municipalities in which the Go to Eat campaign was implemented.

Figure 14 summarizes the results of the re-estimation of the event study model with the one-period lagged

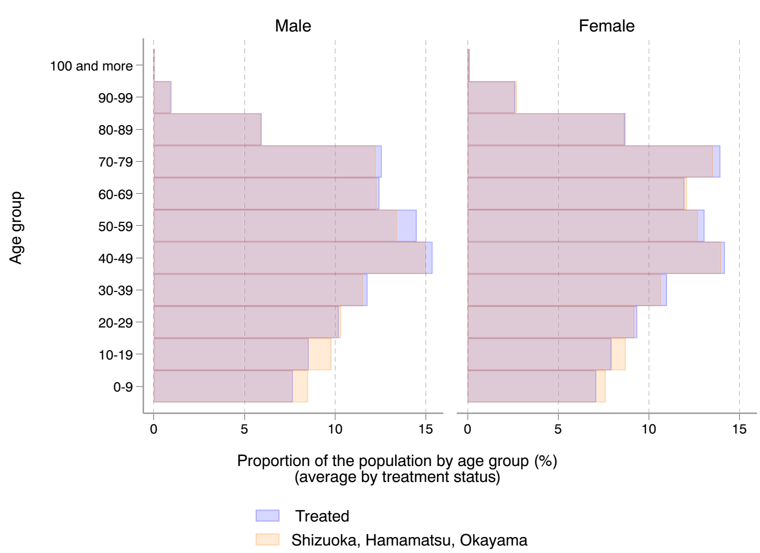


Fig. 11 Proportion of population by age group in 2020. Notes: The bars indicate the average value of the proportion of the population in an age group to the total population by gender and area

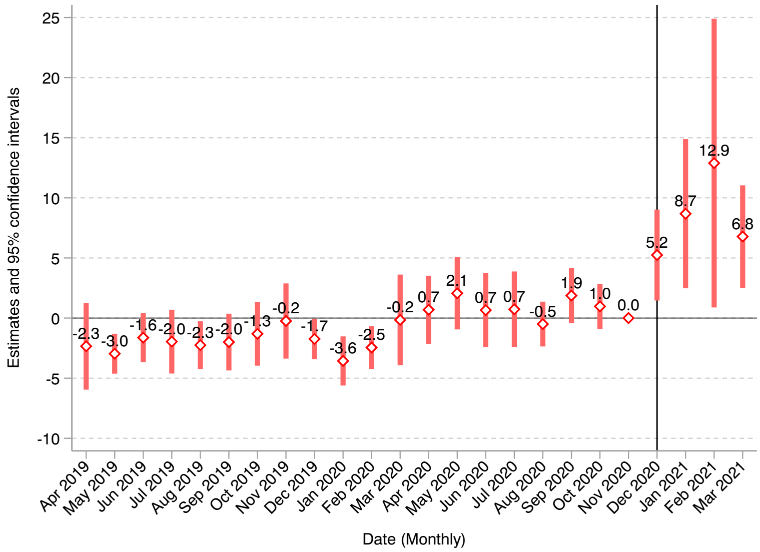


Fig. 12 Event study for restaurant openings (excluding Chiba, Saitama, Kawagoe, Kitakyushu, and Kurume). Notes: The diamond symbols indicate the estimated coefficients on the cross-term of the treatment dummy and the monthly dummy variables, and the bars are the 95% confidence intervals for the estimates. We set November 2020 as the reference month. The confidence intervals are calculated using standard errors robust against municipality-level clustering

municipalities' number of COVID-19 positive cases. We use the one-period lagged municipalities' number of COVID-19 positive cases and its squared term, the cross-term between the one-period lagged municipalities' positive cases and the restaurant type dummy, and the cross-term between the squared term and the restaurant type dummy as the control variables in addition to the basic models.

As discussed in Section 4, we use the two dimensions of the treatment status, the type of restaurant (dine-in or other types of restaurants) and the region (the areas with and without the declaration of the state of emergency). As such, we could implement a difference-in-differences-in-differences (DDD) model as follows:

$$\begin{aligned} y_{mit} =& \alpha_0 + \alpha_1 TreatRegion_m + \alpha_2 DineIn_i \\ &+ \alpha_3 After_t \\ &+ \alpha_4 TreatRegion_m \times DineIn_i + \alpha_5 DineIn_i \\ &\times After_t + \alpha_6 TreatRegion_m \times After_t \\ &+ \alpha_7 TreatRegion_m \times DineIn_i \times After_t \\ &+ x'_{itm}\gamma_3 + \eta_{3m} + \phi_{3it} + u_{3itm}. \end{aligned} \tag{3}$$

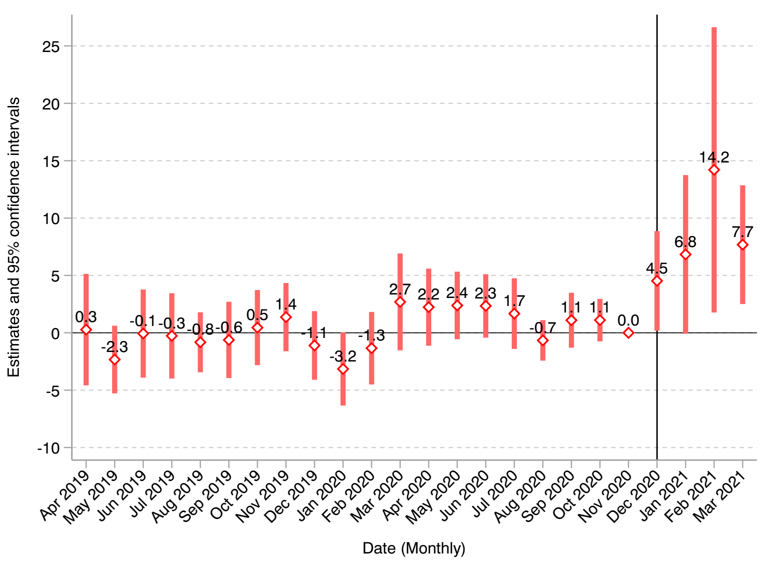
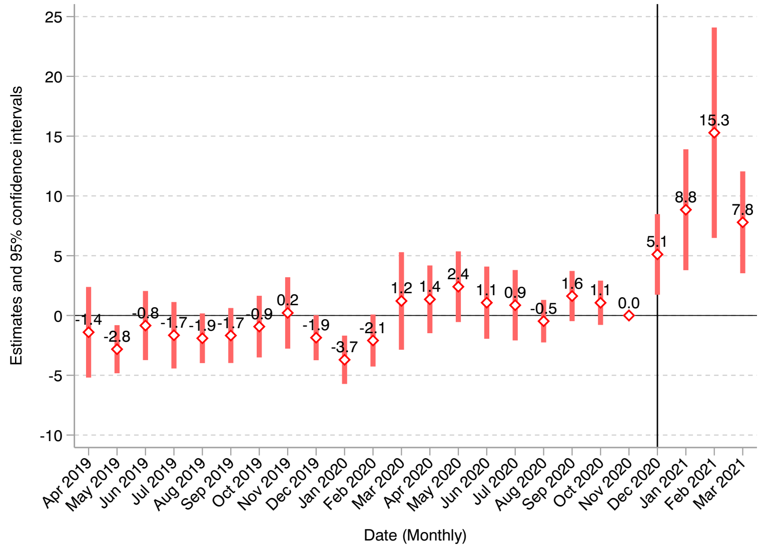
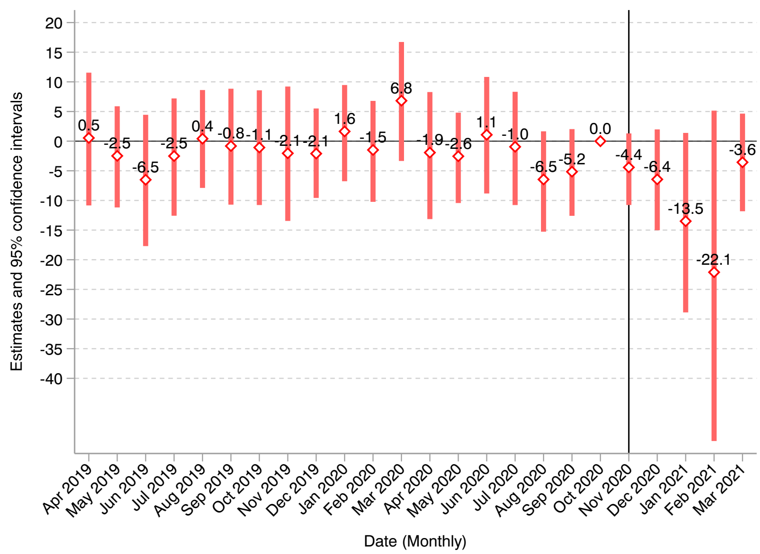


Fig. 13 Event study for restaurant openings (excluding Shizuoka, Hamamatsu, and Okayama). Notes: The diamond symbols indicate the estimated coefficients on the cross-term of the treatment dummy and the monthly dummy variables, and the bars are the 95% confidence intervals for the estimates. We set November 2020 as the reference month. The confidence intervals are calculated using standard errors robust against municipality-level clustering

Fig. 14 Results of event study by adding one-period lagged municipalities' number of COVID-19 positive cases. Notes: The diamond symbols indicate the estimated coefficients on the cross-term of the treatment dummy and the monthly dummy variables, and the bars are the wild bootstrap cluster if 95% confidence intervals are robust against municipality-level clustering calculated using user-written Stata command "boottest"Roodman et al. (2019). We set November 2020 and October 2020 as the reference month for **a** and **b**, respectively



(a) Restaurant Openings



(b) Restaurant Closings (reference: October 2020)

$TreatRegion_m$ is a dummy variable taking one if observations are the area where the states of emergency were declared in our sample period. $DineIn_i$ is a dummy variable taking value one if observations are the number of dine-in restaurants. The definitions of the other variables and the notations follow Eq. (1).

Table 13 summarizes the estimation results of the DDD model. We only report the estimates of the DDD term. The DDD estimate is positive and statistically significant at the 1% level, and its magnitude is 5.205. The magnitude of the estimate can be interpreted so that, compared to the average value for dine-in restaurants in the region with a declaration before the support expansion, the number of restaurant openings increased by around 35.8%. The magnitude of the DDD estimate is comparable to that of the DID estimate in column 1 of Table 5.

Tables 14 and 15 summarize the estimation results using the average amount of financial support per day instead of the DID term. The estimated coefficients of

Table 13 Results of the DDD estimation (restaurant openings)

	(1)
DDD estimates	5.205***
	(1.364)
Number of observations	3936
Pre-expansion mean among treated	14.549
Magnitude in percentage change (%)	
(compared to the pre-expansion mean)	35.78
Number of municipalities	82

The dependent variable is the number of newly approved restaurants. Standard errors robust against municipality-level clustering are shown between parentheses. All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of positive COVID-19 cases and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-level restaurant type fixed effects, and monthly fixed effects. We also add the first and second-order terms of the DDD term. Inferences: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14 Effects of the amount of financial support on restaurant openings

	(1)
Average daily amount of financial support	0.849**
	(0.390)
Number of observations	3936

The dependent variable is the number of newly approved restaurants. The unit of the average daily amount of the financial support is JPY 10,000. Standard errors robust against municipality-level clustering are shown between parentheses. All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of positive COVID-19 cases and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-level restaurant type fixed effects, and monthly fixed effects. Inference: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15 Effects of the amount of financial support on restaurant closings

	(1)
Average daily amount of financial support	−1.317
	(0.047)
	[−2.638, −0.0154]
N	1872

The dependent variable is the number of restaurants having gone out of business. The unit of the average daily amount of the financial support is JPY 10,000. The wild bootstrap cluster p-values and the wild bootstrap cluster with 95% confidence intervals are between parentheses and square brackets, respectively, and are calculated using user-written Stata command "boottest"(Roodman et al., 2019). All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of positive COVID-19 cases and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-level restaurant type fixed effects, and monthly fixed effects

Table 16 Robustness check: prefecture monthly fixed effects

	Entry		Exit	
	(1)	(2)	(3)	(4)
Treated × After	4.566***	3.875***	−5.028	−5.028
	(1.057)	(1.145)		
			⟨0.079⟩	⟨0.079⟩
			[−10.55, 0.566]	[−10.55, 0.565]
Number of observations	3936	3936	1872	1872
Pre-expansion mean among treated	14.549	14.549	16.747	16.747
Magnitude in percentage change (%)				
(compared to the pre-expansion mean)	31.38	26.63	−30.02	-30.02
Number of municipalities	82	82	39	39
Prefecture monthly fixed effects	No	Yes	No	Yes

The dependent variable is the number of newly approved restaurants and the number of restaurants having gone out of business. Standard error robust against municipality-level clustering is shown between parentheses in columns 1 and 2. In columns 3 and 4, the wild bootstrap cluster p-values and the wild bootstrap cluster with 95% confidence intervals are between angle brackets and square brackets, respectively, and are calculated using user-written Stata command "boottest"(Roodman et al., 2019). All specifications are estimated using a fixed effects model and include the one-period lagged term of the number of positive COVID-19 cases and its squared term, the cross-term between the one-period lagged term and the restaurant type dummy, the cross-term between the squared one-period lagged number of positive cases and the restaurant type dummy, the cross-term of the treatment status dummy and month dummy variables, the cross-term of quarter and prefecture fixed effects, municipality-level restaurant type fixed effects, and monthly fixed effects. Inferences for columns 1 and 2: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the average daily amount are statistically significant at the 5% level for both restaurant openings and closings. The results suggest that a one-unit (JPY 10,000) increase in the daily amount of the financial support increases restaurant openings by 0.85 and decreases by 1.3 restaurant closings.

Table 16 summarizes the estimation results of the DID estimation on restaurant openings and closings with and without prefecture monthly fixed effects (FEs). The prefecture monthly FEs can account for unobserved prefecture monthly characteristics, such as other industry support policies implemented by prefectures and the COVID-19 cases in neighboring prefectures, which could have affected both the decision of the expansion of financial support and restaurant entries and exits. By adding prefecture monthly FEs, we can control for the potential endogeneity bias resulting from these scenarios. To assess the extent to which these scenarios may introduce bias to our estimates, we estimated the DID models both without the prefecture monthly FEs (columns 1 and 3) and those with the FEs (columns 2 and 4). According to Table 16, adding the prefecture monthly FEs does not affect the DID estimates for both restaurant openings (column 1 versus column 2) and restaurant closings (column 3 versus column 4)[60], suggesting that the potential endogeneity bias resulting from unobserved prefecture monthly characteristics is not serious in our setting.

B.3 Descriptive statistics for discussion

Immediately after the expansion of financial support was announced, there was an increase in the number of restaurants that opened in time to apply for financial support among the areas with low total rent for vacant restaurants. Figure 15 summarizes the percentage of new dine-in restaurants in locations where other licenses have been approved in 2020 compared to the same period in the previous year. We use half-months as the time variable and plot the percentage by the total rent of the area. We also plot the percentage for other types of restaurants for comparison. Among the regions with relatively lower costs to open restaurants, the percentage of dine-in restaurants that started operations in locations where other restaurants were approved in the past increased more than twice compared to the same period in the previous year between

[60] Since the data for restaurant closings include three prefectures, the estimates are almost the same

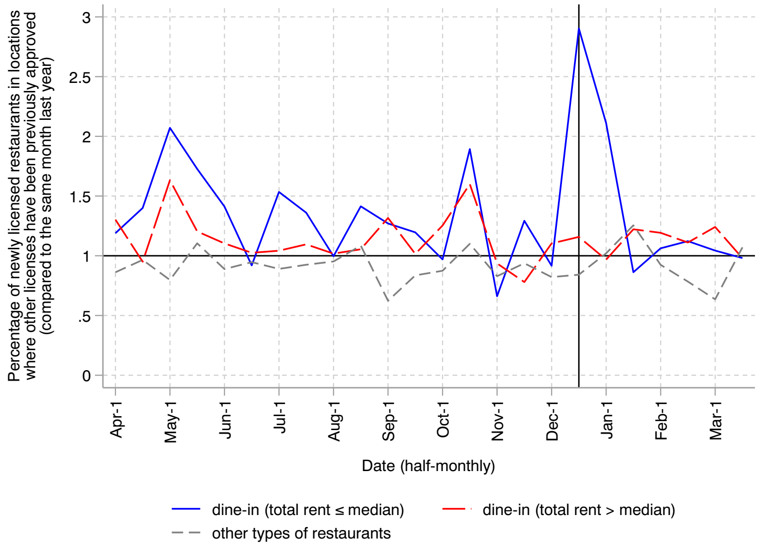


Fig. 15 Percentage of newly approved restaurants in locations where other licenses have been previously approved compared to the same month in the previous year. Notes: The municipalities whose data on approved business licenses and discontinuation of business are available from FY2017 and FY2020 were utilized for this figure

the last half of December 2020 and the first half of January 2021, just after the prime minister announced that the national government would support local governments to expand the financial support for reducing the business hours of dine-in restaurants.

Figure 16 shows the proportion of newly approved dine-in restaurants that submitted notifications of discontinuation within 30 days after getting approved. We use the municipalities that we have access to data on restaurant openings and closings since April 2021 (Yokohama, Nakano, Bunkyo, Koto, Shibuya, and Sumida) to calculate the proportion of newly approved dine-in restaurants that closed within 30 days after they got approved. We exclude the dine-in restaurants which

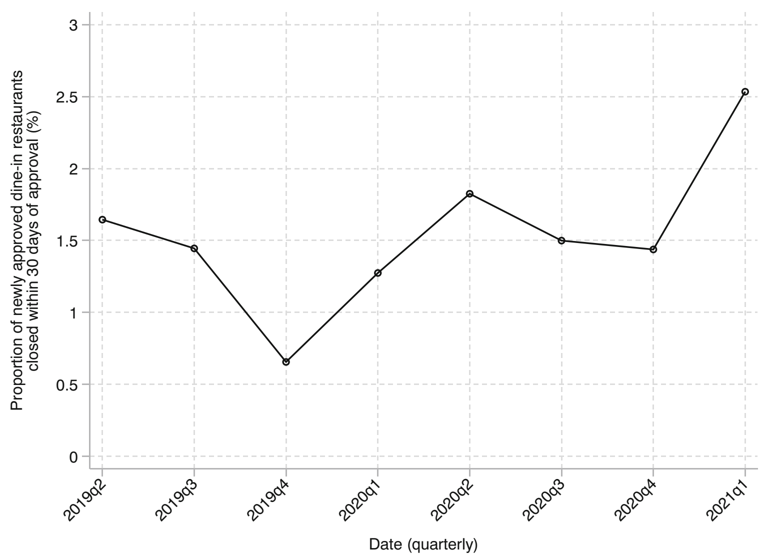


Fig. 16 Proportion of newly approved dine-in restaurants that closed within 30 days after getting approved. Notes: We use the municipalities that had access to data on restaurant openings and closings since April 2021 (Yokohama, Nakano, Bunkyo, Koto, Shibuya, and Sumida) to calculate the proportion of newly approved dine-in restaurants that closed within 30 days after they got approved. We exclude the dine-in restaurants that intended to operate on a short-term basis, such as restaurants opening for festivals

Table 17 Number of dine-in restaurant openings by month and year

	2018	2019	2020	2021	Pre-pandemic average	Pre-pandemic average versus after Dec. 2020
December	285	276	381		281	135.83%
January	238	224	239	331	234	141.65%
February	273	287	284	335	281	119.08%
March	381	329	437	457	382	119.53%
April	407	372	439	389	390	99.87%

We use the municipalities with access to data on restaurant openings and closings since April 2021 (Yokohama, Nakano, Bunkyo, Koto, Shibuya, and Sumida) to calculate the number of dine-in restaurant openings. The blue cells indicate the pre-pandemic period and the orange cells indicate the period after December 2020. When we use April 2020 to calculate the pre-pandemic average for April, the number of restaurant openings is around 96% of the pre-pandemic average

intended to operate on a short-term basis, such as the restaurants opened for festivals.

Approximately 1.2% of newly approved dine-in restaurants closed within 30 days after they got approval in FY 2019 and the proportion increased to 1.8% in FY2020. According to Fig. 16, there is an increase in the proportion in the last quarter of FY2020 ("2021q1"): around 2.5% of newly approved dine-in restaurants closed within 30 days of approval. Even in the last quarter of FY2020, the proportion has variation: 0.9, 3.0, and 3.3% for January, February, and March 2021, respectively. The number of new positive COVID-19 cases in FY2020 showed a large increase in January 2021 and then decreased (Fig. 1). Entrepreneurs might have expected that the declaration of the state of emergency to be lifted soon afterward, resulting in the end of the provision of the financial support for dine-in restaurants to reduce their business hours or a reduction in the amount of support. The state of emergency was lifted on March 21, 2021. The financial support was in effect during April 2021 but the amount per day was scaled down from JPY 60,000 to JPY 40,000 (a 33.3% decline) in Tokyo and Kanagawa in early April.[61] The rapid increase in the proportion of newly approved dine-in restaurants that closed within 30 days after they got approved in February and March 2021 may reflect the exits of those entrepreneurs from the market.

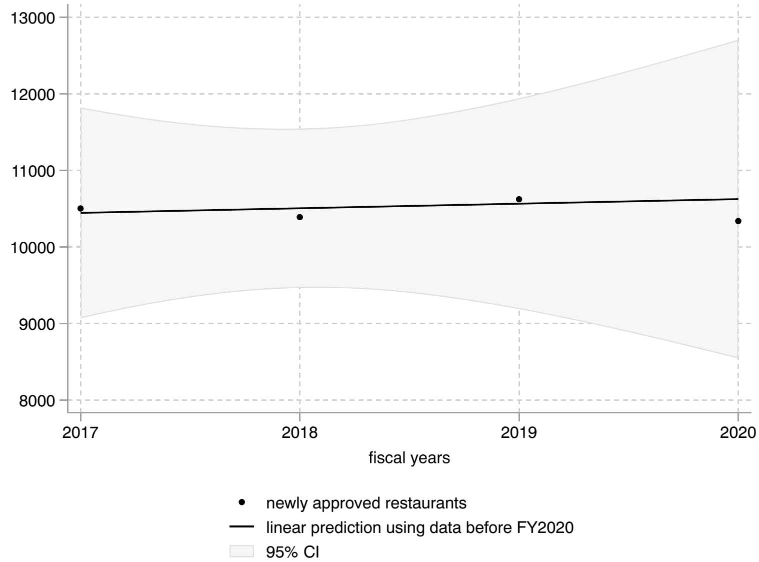
Table 17 summarizes the number of dine-in restaurant openings by month and year. We use the municipalities with access to data on restaurant openings and closings since April 2021 (Yokohama, Nakano, Bunkyo, Koto, Shibuya, and Sumida) to calculate the number of dine-in restaurant openings. The blue cells indicate the pre-pandemic period, and the orange cells indicate the period after December 2020. The number of dine-in restaurant openings was 119–142% more compared to the pre-pandemic average from December 2020 to March 2021, and was comparable to the pre-pandemic average in April 2021. This may be because the amount of financial support per day was scaled down by 33.3% in April 2021.

Figure 17 shows the change in restaurant openings and closings between FY2017 and FY2020 using all types of restaurants in the municipalities where data on both openings and closings are available.[62] The figure includes the predicted trends of restaurant openings and

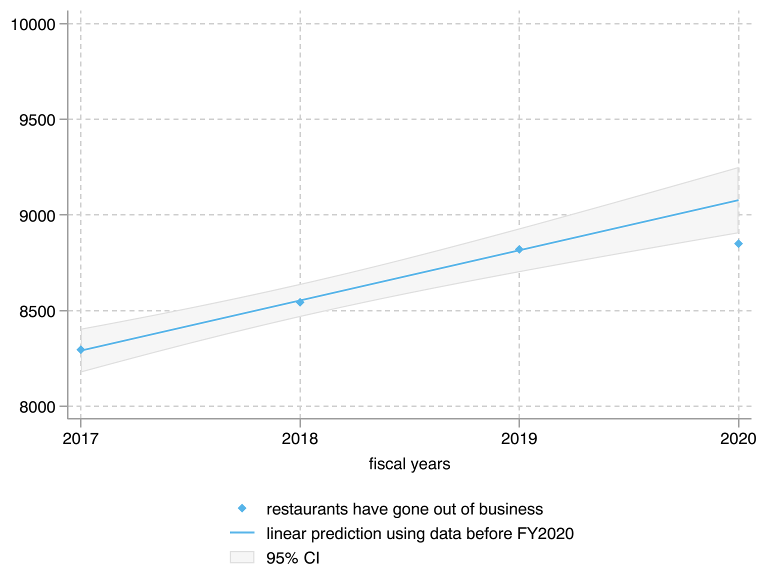
[61] From the middle of April, the amount of the financial support depended on the daily sales of each restaurant. If the daily sales were below JPY 100,000, the amount of the financial supports was JPY 40,000. We assume the number of business days in a month to be 20 and 30 days. Then, the daily sale of JPY 100,000 or below corresponds to the monthly sale of JPY 2 million or below and JPY 3 million or below for 20 and 30 days, respectively. According to the Survey on Business Start-ups, the proportion of dine-in restaurants whose monthly sales were less than JPY 2 million and less than JPY 3 million was 81% and 92%, respectively. As such, for most dine-in restaurants, the amount of the financial supports could have been JPY 40,000.

[62] We used data from Shibuya Ward, Shinjuku Ward, Sumida Ward, Taito Ward, Bunkyo Ward, Katsushika Ward, Koto Ward, Nakano Ward, Yokohama City, Kawasaki City, Kitakyusyu City, and Kurume City.

Fig. 17 Change in restaurant openings and closings between FY2017 and FY2020. Notes: We calculate the total number using all types of restaurants in the municipalities where data on both openings and closings are available from FY2017 to FY2020



(a) Restaurant openings



(b) Restaurant closings

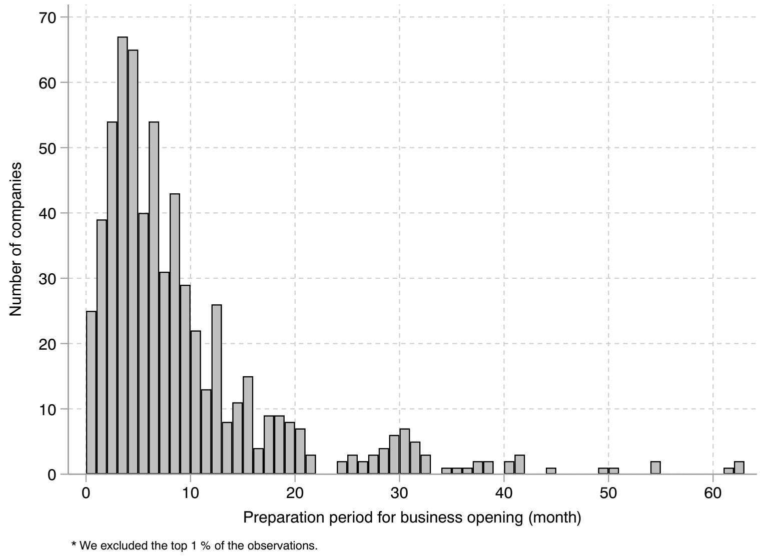
closings, using data from FY2017 to FY2019, along with their 95% confidence intervals.

Despite the decreased demand for eating-out services due to the COVID-19 pandemic, the number of restaurant openings during the pandemic (FY2020) did not deviate from the pre-pandemic trend (Fig. 17a). Furthermore, the number of restaurant closings during the pandemic is 2.5% smaller than its value predicted by the pre-pandemic trend, and it is statistically significant at the 5% level (Fig. 17b).

B.4 Descriptive statistics of restaurant openings in Japan

This appendix provides basic statistics on restaurant openings in Japan using the Survey on Business Start-

Fig. 18 Distribution of preparation period for business openings. Notes: We excluded the top 1% of the observations for clarity



ups conducted by the Japan Finance Corporation (JFC) Research Institute. The Survey on Business Start-ups is an annual survey for firms financed by the JFC between April and September 1 year before the survey year and that had been in business for 1 year or less at the time of the loan. The survey is conducted every July through mail and collects data on the attributes and careers of the managers of new firms, their preparation for opening a business, and the status of their employees. We use the Survey on Business Start-ups for 2018, 2019, and 2020, the response rates being 21.0%, 25.9%, and 30.9%, respectively.

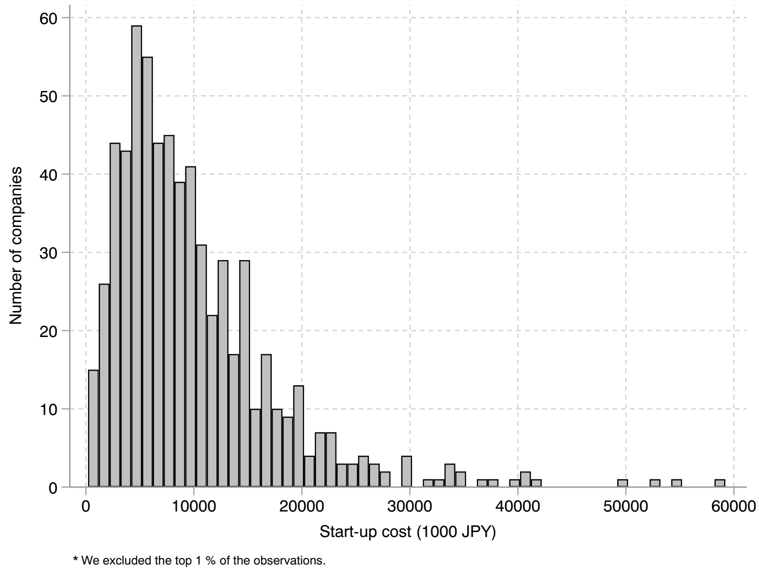
Since the survey targets not only restaurants but also firms in other industries, we restrict the sample to those considered privately owned dine-in restaurants as follows. First, we restrict our sample to privately owned firms in the "accommodation and food services" industry. Then, to exclude accommodations from the analysis sample, we keep firms whose main place of business is a store for consumers. Since, according to an official report of the survey, takeout/delivery food services are included in "retail business," the sample restricted by the above procedure is considered to be privately owned dine-in restaurants.[63] We also restrict our sample to dine-in restaurants opened by December 2019 to calculate the basic statistics of restaurant openings at ordinary times, that is, during the pre-pandemic period.

Figure 18 shows the distribution of the preparation period for business openings among dine-in restaurants. We have data on years and months when restaurants began preparing to open for business and when restaurants were launched. Using those data, we calculate the monthly level preparation period for business openings. For restaurants whose months for the beginning of the preparation to open for business and for being launched are the same, we set the value zero for the preparation period. As we have access only to the monthly level data, a restaurant that began preparing to open for business on October 31 and started its operation on November 1 is assigned a value of one for its preparation period. We regard restaurants being assigned zero and one for their preparation periods as restaurants that spent only one month preparing to open for business.

The average and median values of the preparation period are 10 and 6 months, respectively. The proportion of restaurants that spent only one month preparing to open for business is around 9.9%. When we restrict our sample to restaurants that inherited land and/or stores from other firms (including those that went bankrupt or went out of business) at the start of the business, the proportion increases to 12.7%. Similarly, when we restrict the sample to restaurants that inherited equipment from other firms at the start of the business,

[63] Please see the footnote of Figure 10 on page 8 of the official report available at https://www.jfc.go.jp/n/findings/pdf/kaigyo_201119_1.pdf.

Fig. 19 Distribution of total start-up cost (1000 JPY). Notes: We excluded the top 1% of the observations for clarity



the proportion increases to 29.2%. This result indicates that entrepreneurs may be able to start a dine-in restaurant business with a short preparation period, especially if they can inherit other stores and/or equipment.

Figure 19 shows the distribution of total start-up costs to open dine-in restaurants. The average value and median of the total start-up costs are JPY 10.89 million and 8.05 million, respectively. We assume that the monthly financial support for restaurants to reduce their business hours is JPY 1.8 million (JPY 60,000 times 30 days). Then, around 4.4% of dine-in restaurants can be opened with costs below the monthly amount. When we restrict our sample to restaurants that inherited equipment from other firms, including those that went bankrupt or went out of business, the proportion increases to 9.9%.

According to the data, around 21% of the total start-up costs account for operating costs, including food and labor costs.[64] The start-up cost could be reduced if entrepreneurs start operating dine-in restaurants to make money through government financial support rather than from market profits. This is because they would not need to pay for operating costs. In addition, we could exclude franchise fees. After we recalculate the start-up costs by summing costs for the store (purchase cost or rent), interior and exterior cost, and equipment cost, around 12.2%, 29.2%, and 43.9% of dine-in restaurants can be opened with the costs below the amount of the financial support in one month, two months, and three months, respectively (column 1 of Table 18).[65] When we restrict our sample to restaurants that inherited stores and equipment from other firms, the proportion is 32.0% for one month, 48.0% for two months, and 64% for three months (column 4 panels A, B, and C of Table 18). The result suggests that profits from the government's financial support could exceed the start-up costs for entrepreneurs who intend to earn through the government financial support rather than from market profits, especially when they get access to a store and equipment from incumbent and exiting firms.

Finally, we discuss the monthly sales of dine-in restaurants. Figure 20 shows the distribution of monthly sales for dine-in restaurants. To show the monthly sales before the pandemic, we restrict the sample to those surveyed in 2018 and 2019. The average value and median of the monthly sales are JPY 1.44 million and 1.05 million, respectively. This indicates that for more than half of dine-in restaurants, the monthly sales were less than the monthly amount of the financial support for reducing business hours, that is, JPY 1.8 million. Strictly, the

64 We classify the subcategories of the total start-up costs as follows: purchase cost or rent of store, interior and exterior cost, equipment cost, business guarantee deposits and/or franchise fee, and operating cost, including food and labor costs. Each subcategory accounts for 19.4%, 37.8%, 19.7%, 1.8%, and 21.2% of total start-up costs, in the order listed above.

65 We calculated the monthly amount of the financial support when the daily amount is JPY 60,000.

Table 18 Percentage of dine-in restaurants opening at costs below JPY 1.8, 3.6, and 5.4 million (%)

	(1)	Inherited from other firms (2) Land and store	(3) Equipment	(4) Land, store and equipment
A. Less than JPY 1.8 million				
Total start-up costs	4.4	6.8	9.9	9.4
B. Less than JPY 3.6 million				
Total start-up costs	15.5	16.4	19.7	12.5
Store + interior/exterior + equipment	29.2	40.6	48.3	48.0
C. Less than JPY 5.4 million				
Total start-up costs	30.0	35.6	40.8	37.5
Store + interior/exterior + equipment	43.9	53.1	60.3	64.0
Number of observations	659	73	71	32

proportion of dine-in restaurants whose monthly sales are less than the monthly amount of the financial support is 75.4%. The result indicates that three-quarters of dine-in restaurants achieved sales less than the amount of the financial support. As such, we could say that the financial support expanded after December 2020 is exceptional support.

B.5 Opening time of dine-in restaurants that operate mainly during nighttime

This appendix describes the opening time of dine-in restaurants that operate mainly during nighttime. We collected data on restaurants via an online publisher of restaurant reviews in Japan, Tabelog, operated by Kakaku.com, Inc., as of July 26, 2023.[66] Customers and restaurant owners can register restaurants on the Tabelog webpage, with 840,000 restaurants being posted on Tabelog as of July 2023.[67]

We used web scraping with Python to collect information on *izakaya* restaurants, which is a type of dine-in restaurant that mainly operates during nighttime in Tokyo. We obtained data on 33,631 *izakaya* restaurants.[68] Since the data on business hours were not required, there were some missing values. Additionally, since the data were provided in a free format, we converted them to a relatively comparable format. Finally, we had data on business hours for 26,859 *izakaya* restaurants (79.9% of the selected restaurants).

Some restaurants had multiple business hours. For example, a restaurant can open for lunchtime (11:30–14:30) and for dinnertime (17:30–23:00). The *izakaya* restaurants that open for lunchtime are around 28.9% of the sample.[69]

Figure 21 summarizes the opening time of *izakaya* restaurants excluding lunchtime opening.[70][71] The peak opening time is between 17:00 and 17:59 (around 41.6%). Approximately 58.6% of the restaurants open after 17:00, and around 71.8% open after 16:00. Since most *izakaya* restaurants open around 17:00, if a business hour of a restaurant is restricted to 20:00, the business hour is just three hours. The average business hours for *izakaya* restaurants that open after 17:00

66 https://tabelog.com/en/(accessed on July 31, 2023).

67 More than 90 million people accessed Tabelog in March 2023. Please see access statistics of Tabelog at https://prtimes.jp/main/html/rd/p/000000921.000001455.html(only in Japanese)(accessed on July 31, 2023).

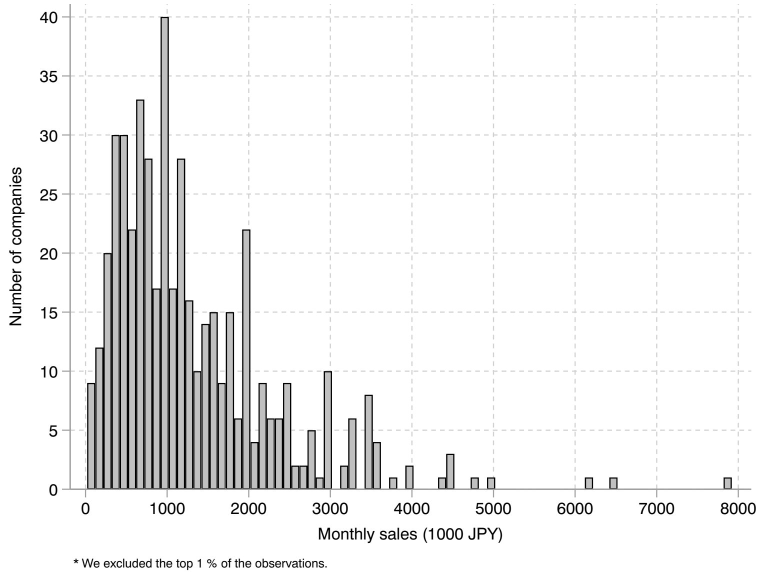
68 In Tokyo, the number of *izakaya* restaurants was 34,159 as of 10:18 on July 26, 2023. We spent around 30 hours from the above date-time to obtain restaurant data, and some posts of restaurants may have been revoked during the web scraping.

69 We defined business hours for lunchtime as business hours less than four hours between 11:00 and 12:59.

70 We calculated the average opening time for each restaurant, excluding opening for lunchtime. For example, assume that a restaurant has four business hours: 11:30–15:00 for lunchtime on a weekday, 18:00–23:00 for dinnertime on a weekday, 11:30–15:00 for lunchtime on a weekend, and 17:00–23:00 for dinnertime on a weekend. Then, the average opening time for the restaurant, except for lunchtime, is 17:30.

71 We also excluded restaurants that are open 24 hours, and those are around 0.4% of restaurants for which we had the data on business hours.

Fig. 20 Distribution of monthly sales (JPY 1000). Notes: We excluded the top 1% of observations for clarity. We restricted the sample to those surveyed in 2018 and 2019 to show the monthly sales before the pandemic



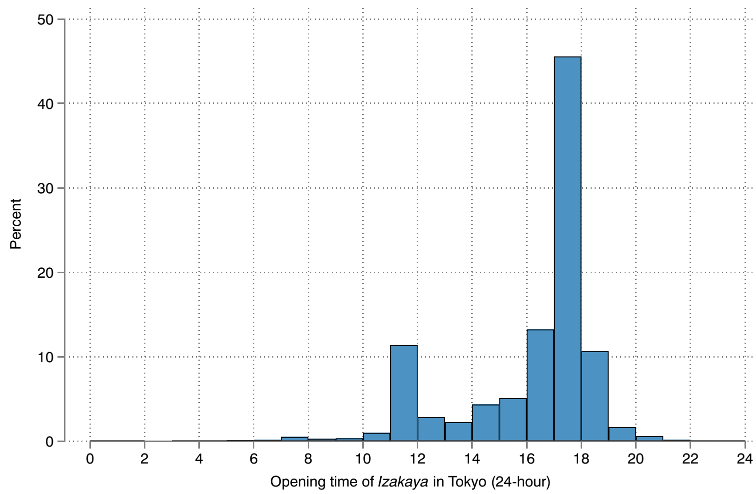


Fig. 21 Distribution of opening time of *Izakaya* restaurants in Tokyo. Notes: The figure summarizes the opening time of *izakaya* restaurants, excluding lunchtime opening. We calculated the average opening time for each restaurant, excluding opening for lunchtime. For example, assume that a restaurant has four business hour slots: 11:30–15:00 for lunchtime on a weekday, 18:00–23:00 for dinnertime on a weekday, 11:30–15:00 for lunchtime on a weekend, and 17:00–23:00 for dinnertime on a weekend. Then, the average opening time for the restaurant for dinnertime is 17:30

is 6.6 hours, and the restriction for dine-in restaurants to close at 20:00 reduces the business hours by half. Therefore, it is possible that dine-in restaurants that operate mainly during nighttime had an incentive to take a break rather than to reduce business hours under financial support for business hour restrictions.[72]

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[72] Note that the opening time is based on data from the post-pandemic period. In July 2023, most measures against the pandemic were removed, and restaurants started operating without any restrictions. As such, we could consider that the restaurants in July 2023 operated almost the same as in the pre-pandemic period.

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