Energy Economics 143 (2025) 108256

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Characteristics of green loan users and the green policy mix

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ARTICLE INFO

JEL codes:
G21
G28

Keywords:
Green loans
Public loan programs
Loan screening
Feed-in-tariffs

ABSTRACT

We analyse the usage of government-sponsored green loans under a feed-in-tariffs scheme and document a positive link with borrower financial health. Green loan users have better credit ratings, higher sales growth, and lower leverage. The link remains stable in face of significantly changing conditions for green investments and heightened policy uncertainty. Green loan users exhibit better ex-post performance and lower default probability. Results are in line with the notion that the screening undertaken by the lender matters for efficient green loan provision and highlight the important role of public loan programs in the green policy mix.

1. Introduction

Climate change is a major global challenge that requires concerted action to reduce greenhouse gas emissions and adapt to the impact of a changing climate (Paris Agreement, 2015). Green finance plays a role in supporting these efforts by providing the necessary financial resources for investments into green technologies and infrastructure (Alharbi et al., 2023). Recent green initiatives (e.g., European 2018 Action Plan on Financing Sustainable Growth) have highlighted the need to support the uptake of green financing. Small and medium enterprises (SMEs) are seen as vital players for the green transition, and increasing their access to sustainable finance opportunities has emerged as an important policy issue (e.g., EU 2021 Strategy for Financing the Transition to a Sustainable Economy). For SMEs that typically face constrained access to finance due to informational asymmetry, green loans have become an essential part in governments' green policy mix, often alongside other green policy interventions (e.g., subsidy schemes for green technology adoption).[1]

In recent years, extant literature has emerged which examines the use of corporate green loans and the green lending behaviour of financial institutions.[2] However, there is paucity of research on SMEs' use of green loans. The present study goes some way towards filling this gap. More specifically, using a confidential loan-level dataset from a Japanese government-affiliated lender, we examine the type of SMEs that use green loans, and how their use of green loans is linked to financial performance after borrowing. We choose as a setting a green SME loan program offered by the SME business unit of the Japan Finance Corporation (JFC), which is a large Japanese government-affiliated policy bank with a long history of providing loans to SMEs for environmental purposes. The green SME loan program under investigation was initiated in 2010 as a part of a green policy mix to promote renewable energy production, which included the introduction of a feed-in-tariffs scheme to accelerate investment in renewable energy projects.

A distinctive aspect of our study is our comparison of the

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[1] Green loans are environmentally focused loans that can be used to finance renewable energy project, support energy efficiency measures or fund other initiatives focusing on sustainability and environmental protection. Examples of green loans include loans financing the installation of solar panels on commercial property, the development of renewable energy projects such as wind farms or hydroelectric power plants, or the promotion of energy efficiency of buildings. Principles such as the Green Loan Principles (LMA, 2018) and Regulation 2020/852 (EU, 2020) have established criteria for determining whether a loan qualifies as a green loan. Set out in the Loan Market Association's 'Green and Sustainable Lending Glossary of Terms' (LSTA, 2021), a green loan is any type of loan instrument made available exclusively to finance or refinance, in whole or in part, new and/or existing eligible 'green projects' including renewable energy, energy efficiency, climate change adaptation and green buildings that meet regional, national or internationally recognised standards or certifications.

[2] See Akomea-Frimpong et al. (2022) for a review on products and determinants of green finance provided by banks, and De Haas (2023) for a review on studies on sustainable banking.

https://doi.org/10.1016/j.eneco.2025.108256
Received 14 March 2024; Received in revised form 28 December 2024; Accepted 20 January 2025
Available online 1 February 2025

performance of green loan users over multiple years, enabling us to observe SMEs' use of green loans over the timeline of the feed-in-tariffs scheme. Our sample period covers the full cycle of the scheme from its introduction in 2012 to major reforms beginning from 2014 onwards. This offers us unique insights into how changing investment conditions for renewable energy technology are linked to green loan usage and borrower performance. We focus in particular on the initial phase of the feed-in-tariffs scheme—the so-called "solar bubble". During this phase, the scheme provided for very favourable investment conditions and attracted a large influx of investors of which a non-negligible portion comprised high-risk investors. These investors lacked viable business plans for renewable energy production and later on struggled to survive (Chu and Takeuchi, 2022). In the first part of our analysis, we evaluate the extent to which the pool of JFC green loan users comprises high-risk investors.

Our evaluation allows us to draw implications regarding the effectiveness of the JFC's screening process for high-risk green investors. By screening loan applications, lenders subject applicants to a selection process whereby only those that are judged to be of acceptable creditworthiness are granted a loan. We posit that a screening process effective in distinguishing between creditworthy and uncreditworthy renewable energy investors would translate into a positive and fairly stable link between firm financial health and green loan usage over the course of the feed-in-tariffs scheme. In other words, we would expect an effective screening process to mitigate some of the design issues of the scheme and to prevent firms with unviable business prospects from obtaining a green loan.[3]

Our main data source is a confidential dataset maintained by the SME business unit of the JFC.[4] The dataset comprises information about small and medium-sized firms in Japan which obtained loans (including green loans) from the SME business unit of the JFC. The unit records a number of characteristics for each of its borrowers, including the purpose of the loan, the borrowers' performance and financial risk as well as its location and industry. For each firm, the JFC also assigns an individual risk rating. For our analysis, the main variable of interest is a firm's use of a green loan at a given point in time. The granularity of the data allows us to examine in detail the characteristics of green loan users and how these evolve in light of changing investment opportunities under the feed-in-tariffs scheme. To our knowledge, this data set of corporate green loans is the most comprehensive to date. It allows for analysis at the level of the individual borrower, offering valuable insights into the screening activity of the lender.

To investigate SMEs' use of green loans over the timeline of the feed-in-tariffs scheme, our analysis comprises three parts. We begin our analysis by discussing some stylised characteristics pertaining to green loan users. Next, we estimate a probit model to examine the extent to which various firm-level characteristics (such as financial health) are linked to green loan usage and whether they vary across different phases of the feed-in-tariffs scheme. We complete our analysis with an examination of the ex-ante and ex-post performance of green loan users relative to non-users. Using a propensity score matching approach, we match SME green loan users with similar SME borrowers, and then compare the performance of the two groups of firms over time and across different phases of the feed-in-tariffs scheme. Specifically, we compare the difference in performance of the two groups at the time of loan origination and up to three years after loan origination using an estimation approach in the style of a difference-in-differences estimation.

By way of preview, we observe from the first part of our analysis that SMEs' use of green loans changes with investment conditions for green technologies. The number of green loan users increases when investment conditions are favourable under the feed-in-tariffs scheme (initial phase) and declines sharply when conditions deteriorate (reform phase).

Next, we find from the second part of our analysis that firm financial health (in terms of credit rating, indebtedness, profitability, and tangibility) is positively linked to green loan usage. Firms are more likely to use green loans if they have more growth potential, and are better rated, less leveraged, and more tangible. The positive link between firm financial health and green loan usage changes to some extent with underlying investment conditions. The link is stronger in the first years of the feed-in-tariffs scheme and weakens as investment conditions worsen after 2014. Notably, however, the link remains positive and does not turn negative under less favourable investment conditions.

Finally, the results from our ex-post examination suggest that green loan users perform well after obtaining a green loan relative to other SME borrowers. Specifically, we find that green loan users are more profitable, and are larger in size and have more tangible assets. Our results further indicate that green loan users have relatively better risk-ratings. This is also reflected in green loan users' being less likely to run a deficit or go bankrupt after loan issuance. Our results are robust to using different sets of SME borrowers for comparison.

The results from our analysis provide two key insights. First, the characteristics of green loan users remain fairly stable over time. That is, even in the wake of significantly changing conditions for green investments, green loan users continue to showcase overall good financial health characteristics. Second, this continuity is also reflected in green loan users' ex-post performance, which remains fairly stable throughout our sample period. As such, our results indicate that the green investors who borrowed funds from the JFC under the public green loan program were unlike the high-risk green investors that had entered the market for renewable energy production in the early phase of the feed-in-tariffs scheme. Overall, our findings point to the presence of an effective screening process by the JFC and suggest that the screening function of government-affiliated lenders can play an important role in ensuring that favourable investment conditions created by government green policies are not met with excessive, unsustainable borrowing activity.

Our study relates to several strands of literature. Our study contributes to an emerging literature on green debt. Much of this literature focuses on large corporate borrowers and their use of green bonds (e.g., Flammer, 2021; Tang and Zhang, 2020), syndicated green loans and sustainability-linked loans (e.g., Degryse et al., 2023; Dursun-de Neef et al., 2022; Aleszczyk et al., 2022) or both (e.g., Newton et al., 2022). Existing studies suggest that corporate characteristics are related to green debt use and generally observe a positive relation with characteristics such as size, profitability, environmental attitude, and environmental scores (e.g., Barbalau and Zeni, 2022; Cicchiello et al., 2022; Dursun-de Neef et al., 2022; Flammer, 2021). Yet, evidence for SMEs and their use of green loans is relatively scarce.

Closest to our study is the paper by Accetturo et al. (2022) who find that bank credit availability drives green investments of SMEs that have abundant internal resources and are thus better equipped to finance capital-intensive investments in green technology. In contrast to Accetturo et al. (2022), our loan-level dataset allows us to directly observe whether a loan is for renewable energy investments or for other purposes.[5] Hence we can clearly distinguish between green loan users (users of renewable energy loans) and other SME borrowers. More

[3] Lender-specific factors that affect the availability of loanable funds are likely minor in our analysis since the JFC is a government-owned policy-implementing financial institution with lending schemes defined by government policy. Funded through secure sources like the Fiscal Investment and Loan Program (FILP), the JFC is unlikely to face lending constraints or capital shortages typical of private financial institutions, ensuring consistent loan availability.

[4] See section 2.2 for more on the JFC.

[5] Accetturo et al. (2022) indirectly derive information on SMEs use of bank credit by extracting information about SMEs' green investment activity from SMEs' annual report, rendering it difficult to isolate to whether and to what extent bank credit was indeed used for green technology investment.

generally, we depart from the existing literature in that we examine green loan user characteristics and derive insights about the screening activity of the government-affiliated policy bank and its role in the green policy mix.[6]

Second, our study also relates to an extant literature that examines government green subsidy schemes and their impact on private green investments (Böhringer et al., 2022; Alolo et al., 2020; Ding et al., 2020; Zhang et al., 2019). Such schemes are subject to frequent adjustments as policy goals evolve or adapt, creating considerable uncertainty for investors and financial institutions (Berg et al., 2023; Neuhoff et al., 2022; Ritzenhofen and Spinler, 2016). There is ample evidence that private investors value schemes which provide a secure and predictable investment framework (for a review of the literature see Polzin et al., 2019). Shorter contract durations, more variability in tariff levels, as well as issues related to grid access are found to increase risk and lower returns, making investments in renewable energy less attractive for investors. Moreover, while long-term contract duration and high tariffs—as is common at earlier stages of feed-in-tariffs schemes—are attractive to investors, excessively generous feed-in-tariffs schemes have been shown to raise concerns about the sustainability of the scheme and ultimately discourage investment. The literature also highlights that a better understanding of investors' financing and investment decisions in response to shifts in green policies is important for achieving more effective outcomes (e.g., Wang et al., 2021).[7] Our study adds to this literature by examining financial health characteristics of SME green loan users within a dynamically changing policy landscape. Our findings are in support of Polzin et al. (2019) which emphasise dynamics and uncertainty in the green policy mix and its implication for SMEs' green financing.

Finally, our study links to the extant literature on government-affiliated (state-owned) banks.[8] Within this literature an emerging strand focuses on government-affiliated *policy* banks (state-owned banks that are policy-oriented) and their role in the transformation process towards greener economies (Mazzucato, 2015).[9] Government-affiliated policy banks have been shown to provide a large share of finance for renewable energy projects (Mazzucato and Penna, 2016; Mazzucato and Semieniuk, 2018). These banks can assist in mobilizing private capital for green technology investments by absorbing investment risks (Geddes et al., 2018) but may refrain from financing novel and small-scale green technology investment (Waidelich and Steffen, 2023). Our findings highlight the importance of government-affiliated banks in the green policy mix and call for further research on the screening and monitoring activities of these banks.

This paper proceeds as follows. In Section 2, we provide background information about Japan's feed-in-tariffs scheme and the JFC. Section 3 introduces our dataset in more detail, and outlines our setting as well as our method. In Section 4, we report our results, and Section 5 concludes.

2. Background

2.1. Feed-in-tariffs schemes in Japan

In this section, we provide relevant background information related to feed-in-tariffs schemes. Specifically, we outline how feed-in-tariffs schemes work in general and discuss the specific characteristics of Japan's feed-in-tariffs scheme that are relevant to our study.

Renewable energy production is capital intensive at the initial stage of deployment of the underlying technology. This subjects investors to high up-front costs and makes renewable energy projects less economically viable than conventional energy projects. Feed-in-tariffs scheme are designed to financially support investment in renewable energy production. Under feed-in-tariffs schemes, investors who wish to produce renewable energy (e.g., via solar panels) enter into a power purchase agreement with a utility provider. The agreement obliges the utility provider to purchase electric power (generated by the renewable energy device of the investor) at a fixed price over a long-term period (e.g., 20 years). Utility providers in turn receive a renewable energy subsidy which is borne by the end users who are required to pay renewable energy surcharges. The ultimate aim of feed-in-tariffs is to advance the deployment of technology essential for the production of renewable energy by making investments in renewable energy production more attractive. For instance, when the technology, e.g., solar panels, is more widely used, production becomes more scale-efficient and cost-effective so that prices of renewable energy technology eventually fall and in turn make investment in renewable energy production more attractive for investors.

Feed-in-tariffs schemes have been implemented in over 92 countries (as of 2021; REN21, 2022). In Japan, the scheme was introduced in 2012 shortly after the Fukushima nuclear disaster. The disaster led to a shutdown of several nuclear reactors and a shift in the national stance on energy policies towards renewable energy sources. In 2012 and 2013, the feed-in-tariffs scheme offered investors relatively generous conditions promising good total profits, moderate annual returns on investment, and an adequate payback period (Muhammad-Sukki et al., 2014). This triggered a large influx of investments in renewable energy projects and helped advance the dissemination of renewable energy technology. The share of renewable electricity in the energy mix increased from 9 % in 2011 to 15 % in 2016 (Kimura, 2017).

Despite the increase in renewable electricity usage, Japan's feed-in-tariffs scheme was subject to a number of issues. Early on, concerns were raised that excessive purchase prices increased the burden for citizens and households (Tanaka et al., 2017) who—as end consumers—bore the costs of the scheme. According to official estimates, standard household electricity prices had risen by 0.5 JPY per kWh, or 150 JPY per month (approximately 1.9 USD).[10]

The scheme was also criticised for incentivising firms without viable renewable energy projects to enter the market for renewable energy production (Chu and Takeuchi, 2022). To secure a purchase price, renewable energy projects merely had to be registered but did not need to be operating. The lax approach to certification essentially lead to a large gap between operating and approved renewable energy capacity, and persisted until about 2017 when a tighter regulatory framework came into effect.

Moreover, with the entry of so-called mega solar power generators, issues around insufficient power grid capacity began to surface. In autumn 2014, Kyushu Electric Power, a major Japanese power firm, announced it would withhold all grid connection requests for solar power of more than 10kWh. Other Japanese power firms followed suit

[6] Studying bank relative to market-based green financing (e.g., green bonds), Newton et al. (2022) find that green bank loans are better at shaping environmental (as well as social and governance) performance of corporate borrowers and suggest that the monitoring function performed by the lender plays an important role.

[7] For instance, Werner and Scholtens (2017) document that increased policy uncertainty negatively affects investors' willingness to make green investments.

[8] See for instance La Porta et al., 2002; Sapienza, 2004; Berger et al., 2005; Dinç, 2005; Micco and Panizza, 2006; Behr et al., 2013; Brei and Schclarek, 2013; Cull and Pería, 2013; Carvalho, 2014; Coleman and Feler, 2015.

[9] For a discussion of the role and scope of government-affiliated policy banks (also called *state investment banks* or *national development banks*) in the transformation process towards greener economies, see Mazzucato (2015).

[10] Initial government estimates of the surcharge for 2012 ranged from 0.22 JPY/kWh to a maximum of 0.5 JPY./kWh. In 2016, the surcharge had risen to 2.25 yen per kWh by May of 2016 (Tanaka et al., 2017), and to 2.98 JPY/kWh in fiscal year 2020 (Mortha et al., 2024).

suspending renewable energy purchases in various prefectures. The Japanese government responded with a major revision to the initial feed-in-tariffs scheme. Between 2014 and 2016, emergency measures were taken within the scope of the existing law and were followed by a fundamental review of the existing feed-in-tariffs scheme leading to a substantial reduction in the purchase price. The reduction was not applied retroactively. See Table 1 Column (1) to (3) for the evolution of purchase prices. In 2017, additional reforms came into effect including a bidding system, stricter approval rules as well as changes to the purchasing party.

The changes in purchase prices and reforms to the feed-in tariffs scheme had a significant impact on the profitability of non-residential solar-power investments (Wen et al., 2021). While these photovoltaic systems initially yielded high internal rates of return (IRR), profitability declined as purchase prices dropped. For instance, in 2012, when the purchase price was 40 JPY/kWh, Wen et al. (2021) estimated that the IRR for 500 kW non-residential plants exceeded 10 %, while for 10 kW plants, it ranged from 6 % to 7 %. However, by 2017, after purchase prices had fallen by more than 50 %, the IRR for 500 kW plants dropped to 5 %, and for 10 kW plants, to just 3 %. These price reductions and policy reforms also had broader impacts, contributing to a rise in bankruptcies among solar-power companies starting in 2014 (see Table 1, Column (4) to (6)).[11]

To facilitate our analysis, we divide the feed-in-tariffs scheme into three phases. Each phase is characterised by major policy shifts that had implications for renewable energy investment conditions. The first phase, which we refer to as the *initial phase*, spans the period from 2012 to 2013 and comprises the introduction of the feed-in-tariffs scheme. The *initial* phase is marked by renewable energy projects promising a high business return and a low risk profile. The *initial* phase was also marked by an inadequately designed certification process which provided strong incentives for high-risk investors to enter the market.

With the Kyushu Electric Shock in the latter half of fiscal year 2014, the *initial* phase came to an abrupt end and set off the second phase. This phase is characterised by the introduction of major reforms, eventually culminating in the revision of the legal framework. We refer to this phase, from 2014 to 2016, as the *reform phase*. As major reforms were brought under way, the earnings outlook for firms wishing to enter the renewable energy market declined gradually and rendered excessive revenues of the earlier years increasingly unlikely. Moreover, concerns about grid access guarantees, variability in tariffs and reduced stability in the regulation induced higher levels of investment uncertainty. As such, the reform phase brought about a worsening in the risk-return profile of renewable energy investments.

The final and third phase, which we refer to as the *post-reform* phase, from 2017 until the end of our dataset, 2018, marks the end to Japan's feed-in-tariffs schemes in its original form. During this phase, major reforms took effect and eventually lead to a bottoming out of investment conditions for renewable energy projects. Table 2 provides a timeline of key policy events over the sample period 2012–2018.

2.2. Japan finance corporation

The Japan Finance Corporation (JFC) is a government-affiliated financial institution wholly owned by the Japanese government. Its fundamental principle is the appropriate implementation of policy financing, and under the policy of the Japanese government, the JFC aims to "complement private financial institutions" by "dynamically implementing policy financing through various methods to meet the needs of society" (the webpage of the JFC).

The JFC has three business units, the Micro Business and Individual unit, the SME unit, and the Agriculture, Forestry, Fisheries and Food Business unit, which are successors of the three government-affiliated financial institutions before their merger in 2008.

The SME business unit of JFC provides loans to SMEs for specific policy purposes. More specifically, the JFC provides policy driven loan programs, of which one comprises Loans for Environment and Energy Measures. The other loan programs are: Corporate Revitalization Loans, New Business Development Loans, Safety Net Loans, Loans for Enhancing Corporate Vitality, and others. These programs are further divided into many subprograms.[12] Across these programs, there are a wide variety of conditions to grant loans and their maximum amount (for example, depending on the amount of funds necessary for the relevant purpose). The relevant information is publicly available on the JFC's website. The total amount of loans outstanding of the SME unit of the JFC provided are 6459.2 and 5326.9 billion JPY, respectively at the end of Mach 2013 and 2019 (end of fiscal years 2012 and 2018: from the JFC's website). For comparison, the total amount of loans outstanding for domestic banks in Japan are 429,252.1 and 508,232.0 billion JPY (from the website of the Bank of Japan).[13]

Because the JFC is a government-affiliated financial institution and does not pursue profit, its lending conditions are set in accordance with the principle of balancing income and expenditure. Their interest rates are risk-adjusted, which are based on their internal credit rating, and also depend on the availability of collateral and the terms (duration) of loans. The credit rating is based on borrowers' financial figures and other factors. Loans are in general granted at the request of the borrower as far as the application satisfies the required criteria set out by the JFC (but with risk-adjusted interest rates). Anecdotal evidence suggests that the interest rates for JFC loans are on average lower than those from private banks, and the banks criticize the JFC on crowding out their businesses. However, borrowers of JFC loans typically borrow from private banks as well, mostly because JFC loans are for specific use (like project finance (but with recourse)) and with limits on the maximum amounts. Furthermore, borrowers of JFC loans also need to rely on private banks for various other types of financial services.[14] Also, during crises such as earthquakes and economic downturns, the JFC (together with other government-affiliated banks) act as important providers of liquidity.

For our analysis, we focus on *non-fossil-energy* loans that fall under the category of Loans for Environment and Energy Measures, which the JFC offers for investments in environmental measures that utilize non-fossil energy sources such as solar energy, wind power, geothermal power, hydropower or biomass.[15] For the purpose of our study, we refer to non-fossil energy loans issued by the JFC as *green loans*. We choose the *green loan* terminology because the JFC non-fossil-energy loans are limited to financing green activities and therefore meet one of the key criteria that define a green loan under the Principles of Green Loans.

[11] Small-scale, non-residential solar power investors also faced increasing competition from large-scale utility solar as well as residential solar investors. See, for example, Kiso et al. (2022) on how residential solar investors benefited from net-metering.

[12] For example, Loans for Enhancing Corporate Vitality include loans to boost corporate vitality, loans to promote information technology, loans for overseas investment and regional revitalization, as well as for employment promotion.

[13] See Uchida and Udell (2019) for more on government-affiliated banks and financial systems in Japan.

[14] Firms need to transact with private banks because the JFC does not take deposits, and provides only a limited type of financial services, mostly loans.

[15] The non-fossil-energy loans are targeted at SMEs that aim to enter the power generation business but lack sufficient capital. Firms can borrow a maximum loan amount of 720 million yen (5 million USD) and are charged a base interest rate adjusted according to the underlying credit risk, loan maturity, and loan purpose. A key requirement imposed by the JFC for non-fossil-energy loans is that 100 % of the loan proceeds are invested in eligible green activities. To verify the use of proceeds, the JFC conducts on-site inspections by visiting borrowers' locations to assess business and facility conditions and inspecting locations of solar panels and the timing of operations.

Table 1
Purchase prices, new establishments and bankruptcies.

Year	(1) Capacity: <10 kW (10y contract)	(2) Capacity: 10 kW - 1999 kW (20y contract)	(3) Capacity: ≥ 2000 kW (20y contract)	(4)Bankruptcy cases solar-energy companies	(5) Newly established power companies	(6) Newly established solar-energy companies
Tariff	JPY/kWh	JPY/kWh	JPY/kWh	#	#	#
2012	42	40	40	–	–	–
2013	38	36	36	25	1799	1213
2014	37	32	32	36	3283	2536
2015	33	29	29	61	2189	1461
2016	31	24	24	68	1791	1045
2017	28	21	Tendered	82	1988	1146
2018	26	18	Tendered	76	1733	1113
2019	24	14[a]	Tendered	86	1433	852
2020	21	13[b]/12[c]	Tendered[d]	54	1145	675
Total				488	15,361	10,041

This table shows the feed-in-tariffs purchase prices, bankruptcy cases, and number of power and solar energy companies from 2012 to 2020. Columns (1), (2), and (3) report purchase prices for different plant capacities ranging from below 10 kW to more than 2000 kW. Columns (4), (5), and (6) respectively report the number of bankruptcies for solar-energy companies, as well as the number of newly established power companies and solar-energy companies. Bankruptcy is defined as legal liquidation with debts of 10million yen and more. Solar-energy companies include firms that manufacture, wholesale, and retail solar system equipment, as well as solar systems installation work, consulting, and businesses that sell and buy electricity from solar power generation (regardless whether the business is the company's principal or secondary business).
Source: METI 2020 for Columns (1), (2), and (3), and Tokyo Shoko Research for Columns (4), (5), and (6) (no data available for 2012).
[a] changed to 10 kW ≤ PP ≤ 499 kW;
[b] 10 kW ≤ PP ≤49 kW;
[c] 50 kW ≤ PP ≤249 kW;
[d] 50 kW ≤ PP ≤249 kW.

Table 2
Timeline of key policy events.

Timeline	Measures
Initial phase (2012–2013)	
2012	Start of the feed-in tariffs scheme in July under the Renewable Energy Law enacted in 2011.
2013	Cut in purchase price.
Reform phase (2014–2016)	
2014	Kyushu "shock": Kyushu Electric Power announced to withhold grid connection requests for solar power of more than 10kWh. Cut in purchase price.
2015	Termination of the initial three-year preferential period of the feed-in-tariffs scheme. Cut in purchase price. Peak in additional grid-connected solar power installed.
2016	Revision of Renewable Energy Act. Revision of approval scheme. Change of method to set feed-in-tariffs. Change of entities obliged to purchase feed-in-tariffs electricity. Cut in purchase price.
Post-reform phase (2017–2018)	
2017	Revised Renewable Energy Act effective from April 2017. Cut in purchase price. Introduction of tender scheme.
2018	Cut in purchase price.

This table provides a timeline of key policy events of the feed-in-tariffs scheme.
Source: International Energy Agency (IEA), National Survey Report of PV Power Applications in Japan (2012–2018).

3. Data and model specifications

In this section, we describe the source of our data, outline the rationale for choosing our control group, provide descriptive statistics for our sample, and discuss our model specifications.

3.1. Data

We obtain confidential business data from the SME business unit of the Japan Finance Corporation (JFC). The JFC SME business unit records detailed information about loans (loan level data) and borrowers over a number of years after the loan origination (firm level data).[16] We integrate these data to construct a firm-level dataset for our analysis.

The collected information comprise details about a firm's industry and headquarter location, size, sales growth, return on assets, operating deficit, default, loan ratio (leverage), and tangibility. By transforming the dataset, we also obtain data on the length of the lender-borrower relationship between the firm and the JFC SME business unit, and firm age. We further observe borrower credit scores from an internal credit rating conducted by the JFC.

Our primary focus is on firms that secure green loans (non-fossil energy loans). However, it is common for these firms to borrow green loans multiple times and/or combine them with non-green loans, either simultaneously or at different points in time. Because we are interested in the effectiveness of loan screening of the JFC, we select first-time users of green loans by dropping all subsequent years of observations after the firm's first origination of a green loan.[17] Restricting our analysis to observations linked solely to the first loan origination enables us to focus on the JFC's screening process for new green projects, rather than its reassessment of existing ones.[18] Note that even if we conduct the same analysis without limiting it to the first loans, the main results are qualitatively unchanged.[19]

[16] We observe only loans that were actually granted and borrowers whose loan application was successful. We do not observe firms whose loan application was rejected.

[17] This ensures that users of green loans enter the dataset only once and are either classified as a green loan user or a non-user. For instance, if a firm originates a green loan in 2012 and a second time in 2018, we only consider the first loan origination in 2012. For firms using both, a green loan and a non-green loan over the sample period, we keep only the first loan origination with the JFC.

[18] We thank two anonymous referees for this suggestion. The total number of green loan users in 2012–2018 is 3426, and that of the first-time users is 2772.

[19] The results are available upon request.

3.2. Choice of control group

To conduct our analysis, we need to make a decision as to the choice of the control group. That is, we need to decide with whom to compare the group of firms that use a green loan. Our choice is driven by evidence from the finance and banking literature which shows that a firm's decision to finance an investment with debt (i.e., by using a loan) and its decision from whom to borrow are not random.[20] This means that firms which choose to use external debt may be materially different from firms that do not choose (or need) to borrow funds. Thus, it is important to control for these dimensions when choosing a control group.

Table 3 depicts a conceptual categorization of our treatment firms and potential control firms. Firms in group (1a) comprise firms using green loans from the JFC—the primary focus of our analysis. We can classify control firms into three groups (1b), (2a) and (2b). Firms in group (2a) are those using other types of JFC loans. Firms in group (1b) comprise renewable energy investors that do not borrow from the JFC (but may do so from private banks), while firms in group (2b) do not invest in renewable energy and/or not borrow from the JFC.

Our choice of control firms falls to firms in group (2a). These are firms that borrow from the JFC SME business unit and use loans other than the non-fossil energy loans. We argue that these firms are suitable controls because they are: SMEs from Japan; are funded externally under a public loan scheme program offered by the same lender (in this case the JFC); and have applied for and successfully obtained a loan. Choosing firms that meet these characteristics helps ensuring comparability with green loan users because firms have similar underlying characteristics in terms of origin, lender, as well as use of external finance. We refer to these control firms as *non-users* or *control* firms.

There are also compelling reasons to compare green loan users with control firms outside the JFC borrower pool, i.e., those in groups (1b) or (2b). Firms eligible to borrow from the JFC may exhibit distinct characteristics that differentiate them from non-JFC borrowers. Moreover, comparing green loan users with firms in group (1b) could provide insights into the effectiveness of loan screening processes between the JFC and private banks. However, the feasibility of such comparisons depends on data availability. Since data exclusively on firms in group (1b) are unavailable, we instead use an alternative control group that aligns with groups (1b) or (2b). Given the trade-offs of this approach, e.g., limited information for firms in this group, we present its methodology and results in Section 4.3 as part of an additional analysis.

3.3. Sample description

Our *baseline* sample comprises green loan users (1a) and firms of control group (2a) as shown in Table 3 and outlined in Section 3.2. We select the firms of control group in the following process. First, other than the green loans that we focus on (*non-fossil-energy* loans), the JFC provides other types of loans for environmental or energy related purposes, for example, loans for industrial waste treatment or pollution control measures. To ensure that control firms borrow for reasons other than engagement in environmental activities, we exclude such firms. Second, we exclude firms that borrow under non-regular business conditions. These include firms borrowing loans for new enterprise development, safety-net loans and loans for corporate revitalisation measures, or loans targeted at start-ups.

Table 3
Control group.

	(a) Public loan scheme borrowers	(b) Others
(1) Renewable energy investors (firms)	(1a) Green loan users = Users of JFC renewable energy loans	(1b) Non-users = Firms investing in renewable energy AND *not* using JFC loans
(2) Other investors (firms)	(2a) Non-users = Users of *other* JFC loans REGRESSION SAMPLE	(2b) Non-users = Firms *not* investing in renewable energy AND *not* using JFC loans

This table provides a schematic of the control group used for comparison of green loan users.

Third, we exclude firms borrowing loans to alleviate liquidity issues, or firms damaged by natural disasters. We conjecture that if substantially different risk criteria are used to evaluate applications for those types of loans, then these firms may not be suitable controls. Finally, to keep consistency with our selection of first-time users of green loans, we drop all subsequent years of observations after a firm's first loan origination with the JFC. Our final baseline sample comprises 2453 number of green loan users, and 11,816 number of non-green loan users (as control firms) for the period from fiscal year 2012 to 2018.

As an alternative JFC sample, we also use a sample which comprises *all* borrowers using JFC SME loans. This sample includes firms that are excluded from the baseline sample and comprises 16,205 non-green loan users for the period from fiscal year 2012 to 2018. We refer to this sample as the *all* sample.

Table 4 shows the distribution of employee size, industry, and location of the JFC firms (green loan users and non-users) and firms in the Economic Census. The Economic Census provides the most comprehensive corporate statistics in Japan allowing us to map our sample of JFC firms in reference to the "average" Japanese firm. Notably, JFC firms do not comprise firms that are very small or are active in agriculture and fishery. This is because the JFC SME Business unit excludes microbusinesses and firms in agriculture and fishery industries (these are dealt with by the JFC Micro Business and Individual unit and the JFC Agriculture, Forestry, Fisheries and Food Business unit). Furthermore, JFC firms are also relatively more dominant in the manufacturing industry. We attribute this to the fact that the loan programs offered by the JFC provide predominantly funds for equipment. JFC firms, like the average Japanese firm, are predominantly located in economically industrious regions such as Kanto, Chubu and Kansai.

3.4. Methodology

This section explains our empirical framework. Our empirical analysis comprises two parts. In the first part, we use a multivariate analysis to examine the link between firm characteristics and the usage of green loans. Our focus is hereby on examining changes across the three phases of the feed-in-tariffs scheme. In the second part, we compare the ex-post performance of green loan users and non-users.

3.4.1. Usage of green loans

The first part of our analysis examines the link between firm characteristics and green loan usage. To investigate this link, we use a probit model and estimate the following equation:

$$Pr\left(Green\ Loan_{i,t}=1\right)=f\left(\alpha_0+\alpha_1 X_{i,t-1}+\alpha_2 X_{i,t}+\theta_t+\theta_{ind}+\theta_p+\epsilon_{i,t}\right) \quad (1)$$

where $i\ (=1,\ldots,N)$ is the firm (N is the number of firms), $t\ (=2012,\ldots,2018)$ is the index representing the year. $Green\ Loan_{i,t}$ is a variable that is equal to the value of one if a firm uses a green loan and zero otherwise. $Pr(\bullet)$ is the probability that $Green\ Loan_{i,t}$ takes the value of one, the function f represents the cumulative distribution function of the standard normal distribution. The main test variables are $X_{i,t}$ and $X_{i,t-1}$ which comprise firm attributes. We use firm financial attributes that are linked to debt usage according to the literature on corporate finance and banking, and green debt choice. These include leverage, profitability, tangibility, and size (Houston and James, 1996; Krishnaswami et al.,

[20] For instance, Schwert (2018) shows that the formation of relationships between banks and borrower depends on borrower and bank financial health.

Table 4
Sample composition.

Panel A	Green loan users						JFC non-green loan users (baseline)					
	2012		2014		2016		2012		2014		2016	
Total	675	%	814	%	24	%	2776	%	2071	%	1396	%
Number of employees												
0–4	38	5.6	94	11.5	14	58.3	110	4.0	66	3.2	355	25.4
5–9	41	6.1	69	8.5			150	5.4	109	5.3	66	4.7
10–19	87	12.9	99	12.2	3[b]	12.6[b]	293	10.6	269	13.0	152	10.9
20–29	64	9.5	84	10.3			353	12.7	236	11.4	110	7.9
30–49	120	17.8	97	11.9	3	12.5	476	17.1	374	18.1	209	15.0
50–99	143	21.2	121	14.9	2	8.3	620	22.3	425	20.5	238	17.0
100–299	116	17.2	88	10.8	0	0.0	513	18.5	309	14.9	193	13.8
300-	66	9.8	162	19.9	2	8.3	261	9.4	283	13.7	73	5.2
Industry												
Agriculture/Fishery/Mining	2	0.3	10	1.2	0	0.0	4	0.1	5	0.2	3	0.2
Construction	44	6.5	102	12.5	7[b]	29.2[b]	121	4.4	152	7.3	118	8.5
Manufacturing	300	44.4	218	26.8			1353	48.7	941	45.4	594	42.6
Utilities & Transport[a]	71	10.5	82	10.1	4	16.7	215	7.7	186	9.0	168	12.0
Wholesale/ Retail trade	127	18.8	153	18.8	3	12.5	559	20.1	413	19.9	236	16.9
Finance/Insurance	0	0.0	0	0.0	0	0.0	2	0.1	87[b]	4.2[b]	0	0.0
Real estate	9	1.3	25	3.1	10[b]	41.7[b]	169	6.1			46	3.3
Services	122	18.1	224	27.5			353	12.7	287	13.9	231	16.5
Region												
Hokkaido	18	2.7	25	3.1			102	3.7	100	4.8	54	3.9
Tohoku	23	3.4	40	4.9	7[b]	29.2[b]	168	6.1	150	7.2	96	6.9
Kanto	122	18.1	194	23.8			799	28.8	533	25.7	465	33.3
Chubu	135	20.0	143	17.6	3	12.5	515	18.6	371	17.9	238	17.0
Kansai	139	20.6	157	19.3	8	33.3	613	22.1	502	24.2	304	21.8
Chugoku	62	9.2	67	8.2	2	8.3	238	8.6	143	6.9	85	6.1
Shikoku	51	7.6	55	6.8	0	0.0	98	3.5	76	3.7	47	3.4
Kyushu & Okinawa	125	18.5	133	16.3	4	16.7	243	8.8	196	9.5	107	7.7

Panel B	JFC non-green loan users (all)						Economic Census					
	2012		2014		2016		2012		2014		2016	
Total	5359	%	2719	%	1194	%	4,128,215	%	4,098,284	%	3,856,457	%
Number of employees												
0–4	365	6.8	150	5.5	427	35.8	3,136,695	76.0	3,046,806	74.3	2,853,123	74.0
5–9	509	9.5	252	9.3	85	7.1	455,675	11.0	469,759	11.5	448,946	11.6
10–19	898	16.8	470	17.3	143	12.0	258,599	6.3	279,724	6.8	261,652	6.8
20–29	714	13.3	336	12.4	122	10.2	94,115	2.3	100,912	2.5	96,176	2.5
30–49	866	16.2	406	14.9	139	11.6	73,561	1.8	80,820	2.0	77,774	2.0
50–99	870	16.2	375	13.8	131	11.0	56,039	1.4	61,311	1.5	59,249	1.5
100–299	556	10.4	235	8.6	93	7.8	37,636	0.9	41,490	1.0	41,474	1.1
300-	581	10.8	495	18.2	54	4.5	15,895	0.4	17,462	0.4	18,063	0.5
Industry												
Agriculture/Fishery/Mining	11	0.2	6	0.2	2	0.2	26,382	0.6	28,165	0.7	27,368	0.7
Construction	477	8.9	277	10.2	108	9.0	468,199	11.3	456,312	11.1	431,736	11.2
Manufacturing	2095	39.1	968	35.6	430	36	434,130	10.5	417,932	10.2	384,781	10.0
Utilities & Transport[a]	492	9.2	282	10.4	180	15.1	121,982	3.0	122,379	3.0	113,480	2.9
Wholesale/ Retail trade	1328	24.8	628	23.1	219	18.3	930,073	22.5	907,857	22.2	842,182	21.8
Finance/Insurance	4	0.1	0	0.0	2	0.2	32,419	0.8	32,200	0.8	29,439	0.8
Real estate	183	3.4	111	4.1	55	4.6	329,449	8.0	322,573	7.9	302,835	7.9
Services	769	14.3	447	16.4	198	16.6	1,785,581	43.3	1,810,866	44.2	1,724,636	44.7
Region												
Hokkaido	198	3.7	116	4.3	49	4.1	168,922	4.1	166,722	4.1	156,475	4.1
Tohoku	496	9.3	208	7.6	72	6.0	302,481	7.3	301,978	7.4	288,245	7.5
Kanto	1599	29.8	756	27.8	312	26.1	1,236,573	30.0	1,238,165	30.2	1,157,385	30.0
Chubu	924	17.2	466	17.1	222	18.6	788,919	19.1	775,147	18.9	733,488	19.0
Kansai	1152	21.5	648	23.8	289	24.2	753,069	18.2	746,270	18.2	697,783	18.1
Chugoku	364	6.8	168	6.2	78	6.5	250,628	6.1	246,114	6.0	233,302	6.0
Shikoku	150	2.8	83	3.1	31	2.6	146,689	3.6	144,027	3.5	136,367	3.5
Kyushu & Okinawa	476	8.9	274	10.1	141	11.8	480,934	11.6	479,861	11.7	453,412	11.8

This table shows the distribution of the number of employees, industry, and location for the year 2012, 2014, 2016. Panel A reports the distribution for green loan users and non-green loan users (baseline). Panel B reports the distribution for non-green loan users (All) and firms included in the Japan Economic Census.

[a] Electricity, Gas, Heat supply and Water/Telecommunications/Transport and postal activities.

[b] To maintain anonymity, entries with a single firm are combined with others to display the total number of firms.

1999; Cantillo and Wright, 2000; Denis and Mihov, 2003; Altunbaş et al., 2010; Barbalau and Zeni, 2022; Flammer, 2021). We also include non-financial characteristics that the literature associates with firm debt choice, such as age and borrower-lender relationship attributes. Our six financial health attributes are *Rating*, *Loan_ratio, ROA, Tangibility, Size*, and *Sales_growth*. The other two firm attributes are *Age*, and *Borrower-Lender-Relationship* respectively. Our empirical approach uses lagged test variables for *Loan_ratio, ROA, Tangibility, Size*, and *Sales growth* to mitigate endogeneity concerns arising from reverse causality.[21] Table A1 in the Appendix provides a description and definition of the variables that serve as indicators for firm characteristics. We include the following fixed effects: time effects θ_t, industry fixed effects θ_{ind}, and prefecture (location) fixed effects θ_p. Industry fixed effects reflect the industry definition provided by the JFC. The final term $\epsilon_{i,t}$ is an error term.

To analyse the link between firm characteristics and green loan usage across various phases of the feed-in-tariffs scheme, we also use a specification whereby we interact our main test variables with period dummies that take the value of one in the respective period, and zero otherwise. As outlined in Section 2, we distinguish between three different periods—*initial* (2012–2013), *reform* (2014–2016), and the *post-reform* phase (2017–2018). [22] Because interaction terms in probit models may not adequately measure marginal effects (Ai and Norton, 2003), we use an OLS estimation by assuming a linear function for f. The OLS estimation also comprises industry and prefecture fixed effects, as well as period dummies.

3.4.2. Ex-post performance

The second part of our analysis examines firms' ex-post performance—the performance of firms after having obtained a green loan from the JFC. We define firm performance on the basis of our firm characteristics used in the previous part of our analysis. These comprise: *Rating, Loan_ratio, ROA, Tangibility, Size,* and *Sales_growth.* We also use two proxies for firm failure: *Default*, a dummy which is equal to one if a firm is bankrupt and zero otherwise, and *Deficit*, a dummy variable which is equal to one if a firm has negative operating income and zero otherwise. The dummy variables *Default* and *Deficit* are respectively based on information from internal ratings (*Rating*) provided by the JFC and on income statements.

To begin with, we measure a firm's change in performance relative to the year of the loan origination. We calculate the change as follows:

$$\Delta Y_{t+k} = Y_{t+k} - Y_t \text{ with } k = 1, 2, 3. \tag{2}$$

Y denotes the performance indicator and t denotes the year when the loan was originated. We take the difference between the value of Y in the year the loan was made (year t) and the values of Y one, two, and three years later ($Y_{t+1}, Y_{t+2}, Y_{t+3}$). We then transform our green loan usage data from calendar time to event time by designating the year when the firm obtained the green loan (year of loan origination) as time zero. We track the change in firm performance for three periods after the loan origination year.

On the basis of our six performance measures, we then compare the ex-post performance of users and non-users. To determine whether users and non-users differ in their performance, we first use a propensity score matching approach.[23] We match users and non-users based on propensity scores from the probit equation (Eq. 1) using the full set of covariates observed in the year of loan origination. We calculate the scores period-by-period and then select firms from each group with equal or highly similar estimated propensity scores. This ensures that firms in each group have similar initial characteristics at the time of loan origination. In a next step, we compare the two groups. Specifically, we compare the difference in performance at the time of loan origination in the years (up to three years) after loan origination of matched users and non-users. To do so, we use an estimation approach in the style of a difference-in-differences estimation and estimate the average treatment effect (ATE). The ATE allows us to derive information about the extent to which the use of a green loan (relative to another type of loan) is associated with a difference in the trajectory of performance in the years after loan origination.[24]

4. Results and discussion

This section begins with an overview of general trends in the use of JFC green loans and presents summary statistics. We then report and discuss the results from estimating the probit and OLS model for the usage of green loans, and the difference-in-differences model with propensity score matching for the ex-post performance.

4.1. Usage of green loans

Fig. 1**, Panel A** shows the number of JFC green loan users in each year from 2012 to 2018. The number increases sharply with the introduction of the feed-in-tariffs scheme in 2012. In 2014, the trend peaks and is followed by a drastic decline. In the years between 2014 and 2018, green loan usage showcases a much more moderate take up. For reference, we also report the number of (new) non-users over time. The numbers are stable until about 2012, and decline slightly thereafter. Notably, the trend does not mirror the drastic increase in the number of green loan users in the period until 2014.

Fig. 1 also shows in **Panel B** the total amount of green loans issued by the JFC and the number of grid connections. The total amount of green loans sharply dropped after 2014. Grid connections continued to increase until 2015 but dropped drastically thereafter. The trends shown in Fig. 1 suggests that favourable investment conditions created by the feed-in-tariffs scheme drove green loan usage during the *initial* period. The sharp decline in green loan usage after 2014 suggests that investment conditions were less favourable thereafter.

Table 5 presents summary statistics separately for green loan users and non-users in the baseline sample**.** The reported mean values for the whole period show that green loan users have on average better credit ratings, are less tangible, and demonstrate better performance in terms of sales growth relative to non-users. Notably, green loan users are also slightly younger and have a shorter relationship with the lender. Users and non-users show little differences in terms of size, leverage, and return on assets. Difference-in-means tests, reported in the last column of the table, confirm that the observed differences between the two group are also of statistical significance. For reference, we also report summary statistics and difference-in-means tests for the sample comprising all controls.

Fig. 2 shows the year-by-year distribution of green loan users and non-users (baseline sample) with respect to their credit ratings. The plots show that the distribution of the control group does not change over

[21] For variable definitions see Table A1 in the Appendix.

[22] Unreported results indicate that the main conclusion does not change even if we replace these period dummies with year dummies.

[23] Specifically, we use a nearest neighbour matching approach to match users and non-users one-on-one based on propensity scores from the probit equation (Eq. 1). Propensity score matching creates pairs of users and non-users with ex-ante similar characteristics. Comparing firms with different ex-ante characteristics may risk capturing differences in performance that are merely the result of a difference in underlying firm characteristics at the time of loan origination.

[24] Staggered adoption of treatment has implications for causal inference in difference-in-differences (DiD) designs (see Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). While we do not apply a staggered DiD estimator due to the structure of our sample, we acknowledge that alternative approaches could model staggered treatment effects differently. Future research may explore these methods in settings where repeated borrowing is observed. We thank an anonymous referee for this comment.

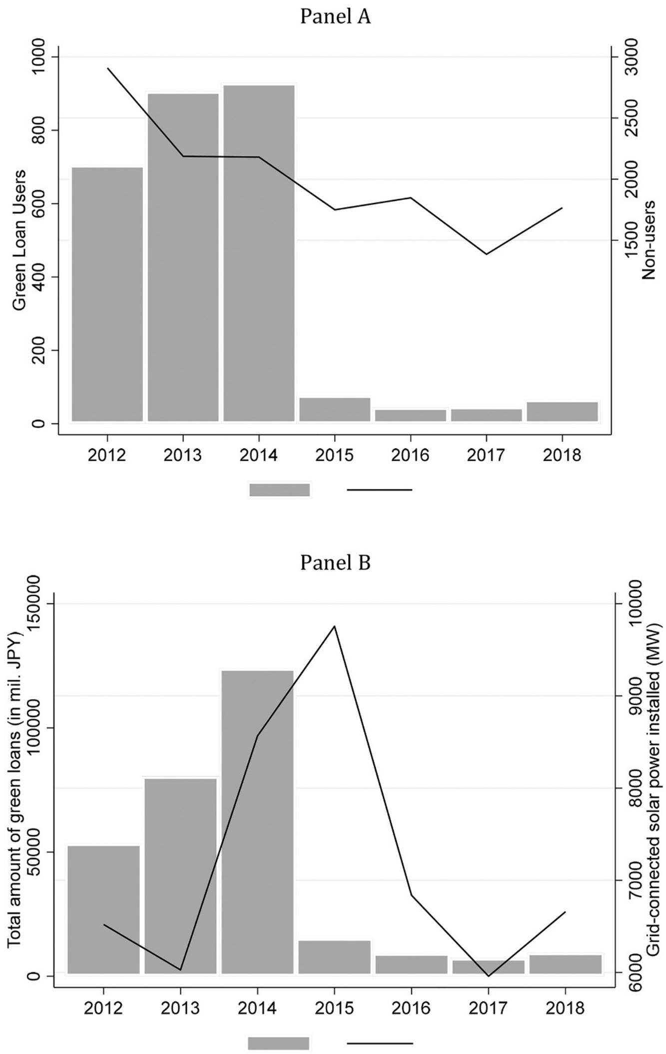

Fig. 1. Green loan usage. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

time. The distribution of users of green loans shifts from favourable to less favourable credit ratings from 2012 to 2015. However, the shifts are not drastic, and the distribution does not change after 2015.

Table 6 **Panel A** reports the results from estimating the probit and OLS model with a dummy variable indicating green loan usage as the dependent variable. In Column (1) and (2), the coefficients for *Rating* are positive; the coefficients for *Tangibility,* and *Relationship* are negative and statistically significant. This indicates that green loan users have better ratings and are less tangible while having a shorter relationship with the lender. Furthermore, the coefficient for *Sales_growth* is positive and statistically significant, suggesting that firms with better growth potential use green loans. For *Loan_ratio* and *Age*, the coefficients are positive, and for *ROA*, the coefficient is negative. However, the coefficients are not (or only weakly) statistically significant. For *Size*, the coefficients are positive and statistically significant. Overall, the results suggest that green loan usage is determined by firm financial health characteristics. Firms with better credit ratings and growth potentials are found to be more likely to use green loans.

By introducing period dummies, we next examine how the link between firm financial health and green loan usage evolves over the course of the feed-in-tariffs scheme. Table 6 Column (3) and (4) report the results. As for the *initial* phase (2012–2013), we observe that green loan users are of better financial health. The coefficients for *Rating* indicate that green loan users have higher ratings. Yet, we also observe that green loan users are less tangible, are older and have shorter borrower-lender relationship. As for the *reform* (2014–2016) phase, we observe that fewer financial health attributes remain statistically significant. The loss in statistical significance indicates that the link between firm financial health and green loan usage is less strong. During the *reform* phase, green loan users have better credit ratings, are larger, and less tangible. They also have higher leverage during this phase. For the *post-reform* phase (2017–2018), we find no specific characteristic other than firm age to consistently define green loan users. For reference, we also report the results from estimating the probit and OLS model using the *all* sample. Overall, the coefficients in Table 6 **Panel B** (Column (5) to (8)) are in line with baseline estimates and suggest a link between green loan usage and firm financial health.

Overall, our results are in line with the notion that the feed-in-tariffs scheme and underlying conditions for green investments affect green loan usage. We find that the link between firm financial health and green loan usage becomes less strong in the face of worsening investment conditions. However, there is no indication that the link turns negative. Green loan usage continues to be positively associated with firm financial health over the course of the sample period. In this sense, our findings substantiate the narrative that the JFC's pool of green loan users did not comprise many of the poorly performing firms which had entered the market for renewable energy during the early phase of the feed-in-tariffs scheme.

4.2. *Ex-post performance*

Table 7 **Panel A** reports the result from estimating the difference-in-differences model with propensity score matching for the baseline sample. We begin by reporting the results for the whole period. The average treatment effect (ATE) for *ROA* and *Tangibility* is positive and

Table 5
Summary statistics.

		(A)		(B) Baseline			(C) All		
		Green loan users		Non-green loan users			Non-green loan users		
		Obs.	*Mean*	*Obs.*	*Mean*	*Difference (A-B)*	*Obs.*	*Mean*	*Difference (A-C)*
Whole period	*Rating*	2453	10.3	11,816	10.1	0.168***	16,205	9.4	0.814***
	Loan_ratio $_{t-1}$	2453	0.5	11,816	0.5	0.005	16,205	0.5	−0.027***
	ROA $_{t-1}$	2453	0.0	11,816	0.0	0.002	16,205	0.0	0.012***
	Tangibility $_{t-1}$	2453	0.1	11,816	0.1	−0.009***	16,205	0.1	−0.007***
	Size $_{t-1}$ (in mil. JPY)	2453	1724.8	11,816	1690.7	34.090	16,205	1078.3	646.442***
	Sales_growth $_{t-1}$	2453	0.7	11,816	0.7	0.010**	16,205	0.7	0.000
	Age (years)	2453	47.5	11,816	48.9	−1.386**	16,205	43.2	4.314***
	Relation (years)	2453	8.2	11,816	9.9	−1.719***	16,205	6.0	2.177***

This table reports the summary statistics and results from *t*-tests for (A) green loan users and non-green loan users ((b) baseline and (C) all controls), for the whole sample period (2012–2018). See Table A1 for variable definitions. ***, **, *, indicate significance at the 1 %, 5 %, and 10 % level respectively.

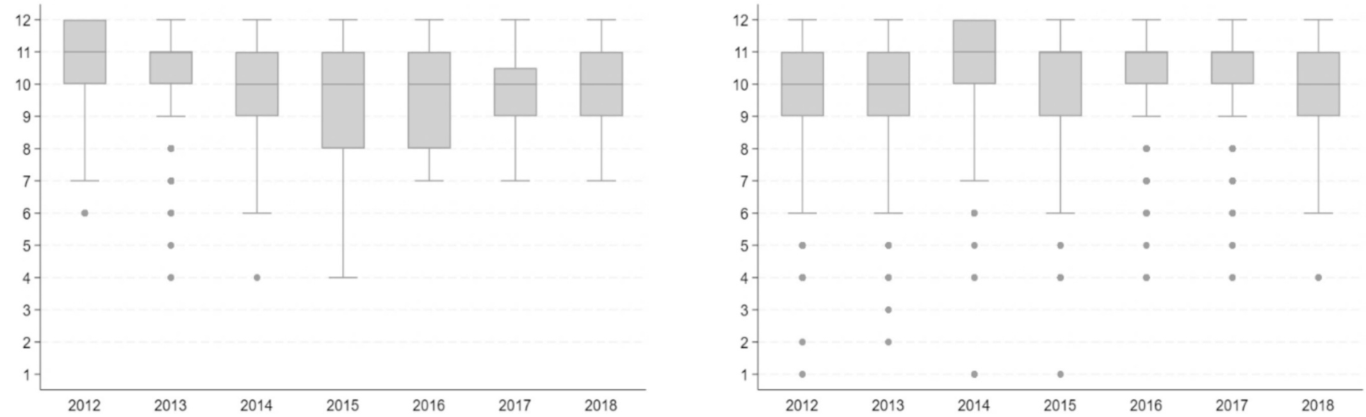

Fig. 2. Year-by-year credit rating distribution.

statistically significant indicating that performance and tangibility of green loan users increased after green loan issuance. We also find that ratings improved ex-post; the positive ATE for *Rating* indicates that ratings for green loan users were better than for non-users. As for the *Loan_ratio*, we observe a positive and statistically significant ATE indicating that green loan users become more leveraged after loan issuance (maybe due to the loan). Furthermore, green loan users are less likely to default or run a deficit as indicated by the negative and statistically significant ATE for *Default* and *Deficit*. Overall, the results suggest that green loan users are on average more profitable, have a more tangible asset base, and are less likely to default or run a deficit than non-green loan users.

Next, we report the results focusing on the three phases of the feed-in-tariffs scheme. For *Loan_ratio, Tangibility, Default*, and *Deficit,* we observe that the sign and statistical significance of the coefficients remain fairly consistent over the three periods (at least when significant). For *Rating* and *ROA*, the coefficients are positive and statistically significant in the *initial* phase of the feed-in-tariffs scheme but turn negative and loose statistical significance thereafter. Overall, this indicates that green loan users performed well ex-post, in particular, during the early phase of the feed-in-tariffs scheme. For reference, we also report the results for the sample comprising *all* controls in Table 7 **Panel B.** Overall, the estimates are not materially different from our baseline results. This alleviates concerns that the composition of the sample and choice of control group firms drives our results.

There are several non-mutually excluding explanations for why green loan users demonstrate good ex-post performance. First, it may be that the investment in renewable energy production (financed by the loan) paid off and helped improving firms' performance metrics. For instance, firms may have benefited from generous purchase prices driving down their energy costs. Additionally, the installation of technological equipment for the production of renewable energy may have translated into a more tangible and even larger asset base, explaining the increase in tangibility and size ex-post. Alternatively, the good ex-post performance of green loan users may also be in part attributable to the screening by the lender. An effective screening process should prevent high-risk firms with unviable business prospects from obtaining a green loan. With effective screening, the pool of JFC green loan users will not comprise this type of high-risk borrowers because those firms will be unable to pass the loan application by the JFC. Finally, it may also be that the good ex-post performance is to some extent the result of self-selection. In the absence of loan application data, we cannot rule out that unviable firms may have refrained from applying for a green loan from the JFC in the first place. However, such a discouragement (self-selection) can also be considered as an outcome of the presence of effective screening. As such, the results suggest that the screening capacity of the lenders can potentially counteract negative incentives set by inadequately designed feed-in-tariffs schemes.

4.3. Ex-post analysis using an alternative control group

In this section, we conduct our analysis by employing an alternative control group. We construct this group of firms using the database compiled by Tokyo Shoko Research (TSR), a private credit information provider. The TSR database comprises information about firm attributes and financial characteristics for around 1.5 million firms each year. Compared with the number of firms for the Economic Census (see Table 4), this coverage is sufficiently extensive, and as such, the database serves as a good representative of SMEs operating in Japan. However, the available variables are limited, and importantly, we lack information to identify whether firms are renewable energy investors. This means that the TSR control group comprises firms in groups (1b) *or* (2b) in Table 3.[25]

The comprehensive coverage of the TSR dataset proves advantageous for our ex-post performance analysis. It allows us to identify suitable matching controls from a pool of firms that is much more heterogenous than the pool of JFC borrowers. Notably, however, this same heterogeneity presents a challenge for analysing green loan usage as we did in the first part of the analysis because a direct comparison between green loan users and a highly diverse set of firms is impractical without further modifications to the dataset.[26] Thus, our analysis with TSR control firms focuses exclusively on evaluating the ex-post performance of green loan users.

We select control firms from the TSR dataset based on multiple criteria and availability of data on firm size, age, industry, location, and

[25] Although the limited information does not allow us to perfectly exclude firms in groups (1a) and (2a) from this control group, we did so by checking the equivalence of the variables for the firms in the TSR database and the green loan users.

[26] Specifically, the significant imbalance between the number of firms in the TSR database (around 1.5 million) and that of green loan users (around 3 thousand) makes it impossible to obtain convergence when estimating a probit model. Moreover, because the TSR database comprises from highly risky to highly profitable firms, from tiny to huge firms, and from wider range of industries, location, and age groups, making it necessary to select firms that deemed appropriate as comparable firms, for instance, based on firm characteristics (e.g., firm attributes and financial health characteristics). However, selecting firms with comparable characteristics from the TSR database would ultimately result in a sample overly similar to the sample of JFC green loan users, undermining the purpose of the probit analysis and, as such, rendering its results meaningless.

Table 6
Green loan usage and financial health.

	(A) Baseline				(B) All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit
Rating	0.0154***	0.0150***			0.0204***	0.0209***		
	(0.0020)	(0.0020)			(0.0013)	(0.0013)		
Rating *12_13			0.0307***	0.0251***			0.0276***	0.0264***
			(0.0032)	(0.0027)			(0.0017)	(0.0018)
Rating *14_16			0.0038	0.0034			0.0157***	0.0165***
			(0.0031)	(0.0030)			(0.0019)	(0.0020)
Rating *17_18			0.0030	0.0050			0.0038	0.0082
			(0.0027)	(0.0087)			(0.0023)	(0.0055)
Loan_ratio $_{t-1}$	0.0193	0.0179*			0.0213**	0.0156**		
	(0.0122)	(0.0104)			(0.0090)	(0.0064)		
Loan_ratio $_{t-1}$ *12_13			0.0089	0.0058			0.0331***	0.0253***
			(0.0154)	(0.0122)			(0.0101)	(0.0078)
Loan_ratio $_{t-1}$ *14_16			0.0678***	0.0642***			0.0395***	0.0376***
			(0.0187)	(0.0172)			(0.0116)	(0.0107)
Loan_ratio $_{t-1}$ *17_18			0.0146	0.0703			0.0023	0.0128**
			(0.0167)	(0.0440)			(0.0041)	(0.0062)
ROA $_{t-1}$	−0.0338	−0.0245			0.0073	0.0260		
	(0.0383)	(0.0328)			(0.0138)	(0.0159)		
ROA $_{t-1}$ *12_13			−0.0872*	−0.0468			−0.0257	−0.0057
			(0.0483)	(0.0393)			(0.0262)	(0.0287)
ROA $_{t-1}$ *14_16			0.0607	0.0703			0.0211	0.0317
			(0.0496)	(0.0538)			(0.0218)	(0.0202)
ROA $_{t-1}$ *17_18			0.1088	0.3148*			0.0924*	0.2855**
			(0.0880)	(0.1892)			(0.0493)	(0.1265)
Tangibility $_{t-1}$	−0.1666***	−0.1325***			−0.0512**	−0.0388		
	(0.0332)	(0.0347)			(0.0233)	(0.0243)		
Tangibility $_{t-1}$ *12_13			−0.2244***	−0.1582***			−0.0591*	−0.0499
			(0.0539)	(0.0473)			(0.0312)	(0.0310)
Tangibility $_{t-1}$ *14_16			−0.1815***	−0.1590***			−0.0556	−0.0506
			(0.0457)	(0.0484)			(0.0356)	(0.0366)
Tangibility $_{t-1}$ *17_18			0.0218	0.1307			−0.0442	0.0531
			(0.0661)	(0.1085)			(0.0579)	(0.0889)
Size $_{t-1}$	0.0080***	0.0095***			0.0293***	0.0255***		
	(0.0028)	(0.0025)			(0.0022)	(0.0020)		
Size $_{t-1}$ *12_13			0.0052	0.0059*			0.0304***	0.0243***
			(0.0046)	(0.0034)			(0.0031)	(0.0026)
Size $_{t-1}$ *14_16			0.0112***	0.0123***			0.0310***	0.0266***
			(0.0041)	(0.0039)			(0.0035)	(0.0031)
Size $_{t-1}$ *17_18			−0.0012	0.0020			0.0088*	0.0209**
			(0.0037)	(0.0110)			(0.0048)	(0.0089)
Sales_growth $_{t-1}$	0.0348*	0.0301**			0.0333***	0.0294***		
	(0.0185)	(0.0147)			(0.0111)	(0.0096)		
Sales_growth $_{t-1}$ *12_13			0.0475	0.0392*			0.0398**	0.0352***
			(0.0314)	(0.0202)			(0.0179)	(0.0134)
Sales_growth $_{t-1}$ *14_16			0.0346	0.0218			0.0433**	0.0338**
			(0.0294)	(0.0213)			(0.0182)	(0.0142)
Sales_growth $_{t-1}$ *17_18			−0.0271	−0.1506			−0.0292	−0.1262
			(0.0233)	(0.1147)			(0.0185)	(0.0819)
Age	0.0132**	0.0093*			−0.0094***	−0.0061*		
	(0.0052)	(0.0049)			(0.0035)	(0.0036)		
Age *12_13			0.0302***	0.0216***			0.0015	0.0054
			(0.0082)	(0.0064)			(0.0049)	(0.0047)
Age *14_16			0.0079	0.0066			−0.0179***	−0.0129**
			(0.0077)	(0.0071)			(0.0053)	(0.0054)
Age *17_18			−0.0140*	−0.0460**			−0.0293***	−0.0682***
			(0.0083)	(0.0224)			(0.0095)	(0.0177)
Relation	−0.0220***	−0.0193***			0.0212***	0.0188***		
	(0.0032)	(0.0027)			(0.0019)	(0.0018)		
Relation *12_13			−0.0137***	−0.0078**			0.0187***	0.0155***
			(0.0051)	(0.0036)			(0.0028)	(0.0023)
Relation *14_16			−0.0317***	−0.0289***			0.0258***	0.0228***
			(0.0047)	(0.0041)			(0.0031)	(0.0028)

(continued on next page)

Table 6 (*continued*)

	(A) Baseline				(B) All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit
Relation *17_18			−0.0032	−0.0299**			0.0129***	0.0295***
			(0.0055)	(0.0144)			(0.0037)	(0.0090)
Constant	−0.2569**		−0.4349***		−0.7794***		−0.9160***	
	(0.1050)		(0.1323)		(0.0716)		(0.0855)	
Period	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industrial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14,269	14,269	14,269	14,269	18,658	18,658	18,658	18,658
R-squared	0.1322		0.1404		0.1119		0.1155	

This table reports the results from the OLS estimation (Column (1), (3), (5), (7)) and the marginal effects from the probit estimation (Column (2), (4), (6), and (8)). Results are reported for the samples comprising baseline controls (A), and all controls (B). The outcome variable is a dummy variable that is equal to one if a firm uses a green loan, and zero otherwise. The test variables include *Rating*, *Loan_ratio* (lagged), *ROA* (lagged), *Tangibility* (lagged), *Size* (log assets, lagged), *Sales_growth* (lagged), *Age*, and *Relationship*. For detailed definitions see Table A1. We include period, industry, and prefecture (location) dummies. Robust standard errors reported in parentheses.
***, **, *, indicate significance at the 1 %, 5 %, and 10 % level respectively.

figures in the financial statements, together with elimination of outliers.[27] Among the 10,339,896 firms (in 2012–2018: around 1.5 million firms each year) in the TSR database, only 2,802,220 (around 400 thousand each year) have financial statements. As a result of the sample selection process, we have 332,579 firms in the control group. Because the majority of SMEs in the TSR database do not have financial statements, the firms in our control group are relatively transparent SMEs.

Using this TSR sample, we then replicate the ex-post analysis with propensity score matching.[28] Table 8 reports the results for the average treatment effects (ATEs).[29] In terms of estimates for the whole period (2012 to 2018), the ATE for *Loan_Ratio, Tangibility,* and *Size* are positive and statistically significant. This indicates that green loan users become more leveraged, more tangible, and larger in terms of size relative to TSR firms after loan issuance. With a view towards the initial, reform, and post-reform phase, we also observe similar links. For instance, ATEs for the *Loan_Ratio* are positive and statistically significant in the initial phase, and sometimes in the reform phase as well, suggesting that green loan users were more leveraged than the average control firm in the TSR sample at that period (Note: TSR controls may include firms with sufficient funds that do not need to borrow). As for *Sales_Growth,* ATEs are negative and statistically significant in the reform and post-reform period (except for t + 1 in the reform period), indicating that green loan users' sales grew less relative to TSR control firms. However, the ATEs for *ROA* are close to zero and not statistically significant, suggesting that lower sales growth did not coincide with a decline in overall profitability. As for *Size,* the positive and statistically significant ATEs during the early phase of the feed-in-tariffs scheme disappears in the reform and post-reform phase. As for *Tangibility,* we do not find statistically significant ATEs (with one exception in the post-reform period).

Overall, these findings indicate that green loan users do not perform materially different from these TSR control firms after loan issuance. As such, the findings based on the TSR sample are in line with our baseline results and further confirm the notion that the screening of the JFC was effective. This interpretation is reinforced by the fact that the TSR control firms are relatively transparent in a sense that they have financial statements available to the public, and likely include those that do not obtain bank loans. Importantly, using the TSR sample, the ex-post analysis provides no substantial evidence that firms using a green loan from the JFC are riskier or of lower financial health than a comparable group of firms.

5. Conclusion

Green loans play an important role in the transition to a more climate-friendly economy by providing funding for investments in new promising technologies. In this study, we analyse the usage of green loans, its determinants and implication for users. Specifically, we examine the usage of green loans by small- and medium-sized firms under a public loan scheme provided by the Japan Finance Corporation. We use as a setting the green loan program of the Japan Finance Corporation during the period when the feed-in-tariffs scheme was introduced and reformed. For our analysis, we make use of reform-induced changes to investment conditions for renewable energy projects, to better understand what factors determine green loan usage.

Our results suggest that green loan usage is positively linked to firm financial health. Green loan users are more likely to have better credit ratings, higher sales growth, and are less leveraged compared to firms not using green loans—attributes that the finance literature typically associates with large public borrowers. Changes in investment conditions triggered by reforms and shocks related to the feed-in-tariffs scheme did not materially affect the link between green loan usage and firm financial health. Our study also uncovers that green loan users perform on average better and are less likely to default or run a deficit in the years following the loan issuance. We attribute these findings in part to the screening activity by the lender.

Overall, our results are inconsistent with the notion that JFC green loan users comprised the kind of problematic firms that had rushed into the market for renewable energy production during the early phase of the feed-in-tariffs scheme. As such, our results suggest that green loan lenders play an important role in their screening capacity. By screening out firms with unviable business prospects, lenders may lessen the

[27] To construct the sample of TSR control firms for matching, we first take several steps to eliminate unsuitable TSR firms. We begin by excluding all TSR firms that lack an ID or have no recorded balance sheet information. We further drop firms with unknown fiscal periods or with fiscal periods not equal to 12 months. We also exclude firms with negative total assets or borrowings, or those whose borrowings or tangible fixed assets exceed total assets. We exclude government or prefectural institutions as well as firms with unknown addresses. We then limit our sample to firms in industries or prefectures that match those of green loan borrowers in any given fiscal year. Finally, we exclude firms with total assets, the number of employees or firm age exceeding the maximum values of those for green loan borrowers' in any given fiscal year, and remove outliers by eliminating firms in the top and bottom 1 % for loan ratio and tangibility, and the top 1 % for ROA and sales growth. We did not limit the TSR sample to firms' first appearances, but the results are qualitatively unchanged even if we do so.

[28] Because using too many dummy variables invites non-convergence in estimating the probit model, we integrated the 25 industry dummies and the 47 prefecture dummies into the 10 industry dummies and 8 region dummies.

[29] We do not (or cannot) report the results for *Rating* and *Deficit*, because the relevant information is not available from the TSR database.

Table 7
Ex-post performance.

Panel A | Baseline

		Rating				*Loan_ratio*			
		ATE	*p*-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	0.104	0.012**	−0.140	2439	0.023	0.000***	0.040	2370
	$t+2$	0.177	0.000***	−0.115	2412	0.023	0.001***	0.031	2344
	$t+3$	0.205	0.001***	−0.102	2339	0.001	0.911	0.011	2253
	$t+1$	0.161	0.022**	−0.151	1499	0.018	0.022**	0.032	1486
2012–13	$t+2$	0.315	0.000***	−0.075	1485	0.030	0.006***	0.028	1456
	$t+3$	0.170	0.040**	−0.127	1459	0.013	0.336	0.011	1413
	$t+1$	0.097	0.072*	−0.113	892	0.033	0.007***	0.055	838
2014–16	$t+2$	−0.144	0.117	−0.176	881	0.019	0.029**	0.038	841
	$t+3$	0.103	0.213	−0.058	861	0.007	0.326	0.009	818
2017–18	$t+1$	0.189	0.728	−0.292	48	0.013	0.101	0.014	46
	$t+2$	−0.439	0.001***	−0.217	46	0.017	0.198	0.013	47

Panel A | Baseline

		ROA				*Tangibility*			
		ATE	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	0.003	0.356	−0.002	2370	0.017	0.000***	0.030	2370
	$t+2$	0.012	0.000***	0.009	2344	0.024	0.000***	0.031	2344
	$t+3$	0.011	0.000***	0.009	2253	0.027	0.000***	0.035	2253
	$t+1$	0.015	0.000***	0.005	1486	0.019	0.000***	0.028	1486
2012–13	$t+2$	0.011	0.001***	0.010	1456	0.021	0.000***	0.027	1456
	$t+3$	0.010	0.002***	0.011	1413	0.020	0.000***	0.029	1413
	$t+1$	−0.004	0.629	−0.015	838	0.027	0.000***	0.033	838
2014–16	$t+2$	0.004	0.296	0.007	841	0.035	0.000***	0.039	841
	$t+3$	0.005	0.109	0.004	818	0.024	0.001***	0.044	818
2017–18	$t+1$	−0.009	0.397	−0.003	46	0.032	0.003***	0.037	46
	$t+2$	−0.015	0.151	0.001	47	0.011	0.392	0.031	47

Panel A | Baseline

		Size				*Sales_growth*			
		ATE[a]	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	19.0	0.250	124.2	2370	0.011	0.111	0.010	2367
	$t+2$	−4.9	0.782	240.4	2344	−0.005	0.359	−0.024	2308
	$t+3$	6.2	0.803	344.3	2253	−0.009	0.130	−0.033	2218
	$t+1$	16.7	0.554	117.8	1486	0.020	0.029**	0.021	1486
2012–13	$t+2$	5.4	0.876	219.5	1456	−0.010	0.266	−0.012	1446
	$t+3$	69.5	0.074*	318.5	1413	−0.018	0.045**	−0.032	1397
	$t+1$	−1.7	0.934	136.1	838	−0.001	0.868	−0.007	835
2014–16	$t+2$	16.7	0.580	277.6	841	−0.021	0.005***	−0.045	816
	$t+3$	−1.7	0.966	390.4	818	−0.026	0.001***	−0.034	799
2017–18	$t+1$	−12.8	0.825	113.1	46	−0.032	0.112	−0.038	46
	$t+2$	11.4	0.766	221.6	47	−0.066	0.000***	−0.034	46

Panel A | Baseline

		Default				*Deficit*			
		ATE	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	−0.002	0.000***	0.000	2439	−0.021	0.176	0.012	2370
	$t+2$	−0.002	0.004***	0.001	2412	−0.080	0.000***	−0.056	2344
	$t+3$	−0.003	0.000***	0.002	2339	−0.129	0.000***	−0.098	2253
	$t+1$	−0.003	0.000***	0.000	1499	0.016	0.403	0.028	1486
2012–13	$t+2$	−0.003	0.006***	0.001	1485	−0.080	0.001***	−0.036	1456
	$t+3$	0.000	0.930	0.001	1459	−0.113	0.000***	−0.076	1413
	$t+1$	−0.001	0.488	0.001	892	−0.046	0.196	−0.014	838
2014–16	$t+2$	−0.003	0.000***	0.001	881	−0.103	0.000***	−0.094	841
	$t+3$	−0.005	0.000***	0.002	861	−0.113	0.000***	−0.141	818
2017–18	$t+1$	−0.002	0.082*	0.000	48	0.160	0.554	0.000	46
	$t+2$	−0.001	0.157	0.000	46	0.371	0.000***	0.000	47

Panel B | All

		Rating	*Loan_ratio*

(*continued on next page*)

Table 7 (*continued*)

Panel B | All		*Rating*				*Loan_ratio*			
		ATE	p-value	Mean	N	ATE	p-value	Mean	N
		ATE	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	0.154	0.008***	−0.140	2439	0.049	0.070*	0.040	2370
	$t+2$	0.299	0.000***	−0.115	2412	0.071	0.028**	0.031	2344
	$t+3$	0.292	0.000***	−0.102	2339	−0.018	0.677	0.011	2253
	$t+1$	0.102	0.168	−0.151	1499	−0.026	0.728	0.032	1486
2012–13	$t+2$	0.277	0.001***	−0.075	1485	0.051	0.205	0.028	1456
	$t+3$	0.325	0.000***	−0.127	1459	0.032	0.505	0.011	1413
	$t+1$	0.097	0.143	−0.113	892	0.075	0.025**	0.055	838
2014–16	$t+2$	0.076	0.475	−0.176	881	0.073	0.037**	0.038	841
	$t+3$	0.336	0.001***	−0.058	861	0.020	0.138	0.009	818
2017–18	$t+1$	0.498	0.386	−0.292	48	0.011	0.015**	0.014	46
	$t+2$	−0.235	0.569	−0.217	46	0.030	0.022**	0.013	47

Panel B | All		*ROA*				*Tangibility*			
		ATE	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	0.022	0.091*	−0.002	2370	0.051	0.000***	0.030	2370
	$t+2$	0.021	0.020**	0.009	2344	0.056	0.000***	0.031	2344
	$t+3$	0.015	0.002***	0.009	2253	0.060	0.000***	0.035	2253
	$t+1$	0.061	0.074*	0.005	1486	0.046	0.000***	0.028	1486
2012–13	$t+2$	0.014	0.066*	0.010	1456	0.061	0.000***	0.027	1456
	$t+3$	0.015	0.062*	0.011	1413	0.051	0.000***	0.029	1413
	$t+1$	−0.012	0.441	−0.015	838	0.032	0.001***	0.033	838
2014–16	$t+2$	0.013	0.349	0.007	841	0.051	0.002***	0.039	841
	$t+3$	0.016	0.018**	0.004	818	0.069	0.000***	0.044	818
2017–18	$t+1$	−0.016	0.144	−0.003	46	0.029	0.000***	0.037	46
	$t+2$	−0.021	0.070*	0.001	47	0.013	0.608	0.031	47

Panel B | All		*Size*				*Sales_growth*			
		ATE[a]	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	22.3	0.144	124.2	2370	0.023	0.106	0.010	2367
	$t+2$	39.2	0.021**	240.4	2344	−0.029	0.040**	−0.024	2308
	$t+3$	54.7	0.017**	344.3	2253	−0.032	0.023**	−0.033	2218
	$t+1$	36.6	0.140	117.8	1486	−0.005	0.782	0.021	1486
2012–13	$t+2$	36.0	0.300	219.5	1456	−0.022	0.078*	−0.012	1446
	$t+3$	57.6	0.356	318.5	1413	−0.032	0.155	−0.032	1397
	$t+1$	21.1	0.170	136.1	838	0.034	0.065*	−0.007	835
2014–16	$t+2$	38.0	0.133	277.6	841	−0.038	0.024**	−0.045	816
	$t+3$	71.1	0.019**	390.4	818	−0.020	0.059*	−0.034	799
2017–18	$t+1$	−41.7	0.006***	113.1	46	−0.130	0.007***	−0.038	46
	$t+2$	−54.2	0.162	221.6	47	−0.135	0.033**	−0.034	46

Panel B | All		*Default*				*Deficit*			
		ATE	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	−0.003	0.000***	0.000	2439	−0.028	0.292	0.012	2370
	$t+2$	−0.005	0.000***	0.001	2412	−0.114	0.000***	−0.056	2344
	$t+3$	−0.006	0.020**	0.002	2339	−0.177	0.000***	−0.098	2253
	$t+1$	−0.003	0.000***	0.000	1499	−0.019	0.497	0.028	1486
2012–13	$t+2$	−0.006	0.000***	0.001	1485	−0.058	0.036**	−0.036	1456
	$t+3$	−0.004	0.273	0.001	1459	−0.134	0.002***	−0.076	1413
	$t+1$	−0.003	0.015**	0.001	892	−0.104	0.001***	−0.014	838
2014–16	$t+2$	−0.004	0.000***	0.001	881	−0.175	0.000***	−0.094	841
	$t+3$	−0.007	0.001***	0.002	861	−0.215	0.000***	−0.141	818
2017–18	$t+1$	−0.002	0.083*	0.000	48	0.144	0.625	0.000	46
	$t+2$	−0.003	0.082*	0.000	46	0.370	0.000***	0.000	47

This table reports the results from estimating a difference-in-differences model with matching. Panel A is based on the sample comprising baseline control firms for matching. The matching method is the propensity score matching. $t+k$ indicates the kth year after obtaining a loan at time t. N indicates the number of green loan users. See Table A1 for variable definitions. ***, **, *, indicate significance at the 1 %, 5 %, and 10 % level respectively.

This table reports the results from estimating a difference-in-differences model with propensity score matching. Panel B is based on the sample comprising all control firms for matching. $t+k$ indicates the k^{th} year after obtaining a loan at time t. N indicates the number of green loan users. See Table A1 for variable definitions. ***, **, *, indicate significance at the 1 %, 5 %, and 10 % level respectively.

[a] ATE for *Size* is in million yen.

Table 8
Ex-post performance - alternative control group.

TSR Sample

		Loan_ratio				*ROA*			
		ATE	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	0.040	0.188	0.040	2394	0.015	0.286	−0.002	2394
	$t+2$	0.067	0.080*	0.031	2367	0.010	0.262	0.009	2367
	$t+3$	0.057	0.033**	0.011	2274	0.031	0.112	0.009	2274
	$t+1$	0.030	0.305	0.031	1509	0.018	0.391	0.005	1509
2012–13	$t+2$	0.116	0.001***	0.027	1478	0.029	0.005***	0.010	1478
	$t+3$	0.061	0.020**	0.010	1433	0.019	0.268	0.012	1433
	$t+1$	0.035	0.211	0.056	839	0.001	0.965	−0.015	839
2014–16	$t+2$	0.071	0.029**	0.040	842	−0.011	0.381	0.006	842
	$t+3$	0.050	0.097*	0.010	819	0.022	0.386	0.004	819
2017–18	$t+1$	0.153	0.291	0.014	46	0.015	0.364	−0.003	46
	$t+2$	0.244	0.049**	0.013	47	−0.039	0.551	0.001	47

TSR Sample

		Tangibility				*Size*			
		ATE	p-value	Mean	N	ATE[a]	p-value	Mean	N
Whole period	$t+1$	0.136	0.011**	0.029	2394	53.0	0.004***	0.125	2394
	$t+2$	0.127	0.001***	0.031	2367	46.6	0.004***	0.242	2367
	$t+3$	0.133	0.003***	0.034	2274	44.1	0.051*	0.345	2274
	$t+1$	0.033	0.580	0.027	1509	93.8	0.014**	0.118	1509
2012–13	$t+2$	0.049	0.383	0.027	1478	72.9	0.054*	0.222	1478
	$t+3$	0.041	0.257	0.029	1433	90.6	0.002***	0.319	1433
	$t+1$	0.122	0.054*	0.032	839	41.3	0.044**	0.136	839
2014–16	$t+2$	0.122	0.035**	0.038	842	11.3	0.598	0.278	842
	$t+3$	0.135	0.009***	0.043	819	4.5	0.864	0.391	819
2017–18	$t+1$	0.306	0.108	0.037	46	134.0	0.152	0.113	46
	$t+2$	0.338	0.145	0.031	47	108.1	0.295	0.222	47

TSR Sample

		Sales_growth				*Default*			
		ATE	p-value	Mean	N	ATE	p-value	Mean	N
Whole period	$t+1$	−0.054	0.462	0.011	2392	0.0000	0.479	0.000	2460
	$t+2$	−0.127	0.001***	−0.024	2331	0.0000	0.448	0.001	2432
	$t+3$	−0.103	0.012**	−0.033	2238	0.0013	0.137	0.002	2358
	$t+1$	−0.064	0.487	0.022	1509	−0.0001	0.045**	0.000	1519
2012–13	$t+2$	−0.048	0.345	−0.011	1468	0.0001	0.421	0.001	1504
	$t+3$	−0.056	0.387	−0.032	1416	0.0079	0.142	0.001	1477
	$t+1$	0.141	0.040**	−0.007	837	0.0000	0.312	0.001	893
2014–16	$t+2$	−0.154	0.003***	−0.046	817	0.0001	0.178	0.001	882
	$t+3$	−0.031	0.471	−0.035	800	0.0001	0.146	0.002	862
2017–18	$t+1$	−0.598	0.046**	−0.038	46	–	–	0.000	48
	$t+2$	−0.624	0.079*	−0.034	46	–	–	0.000	46

This table reports the results from estimating a difference-in-differences model with propensity score matching using the TSR sample. $t+k$ indicates the k^{th} year after obtaining a loan at time t. N indicates the number of green loan users. See Table A1 for variable definitions. Variables *Ratings* and *Deficit* not available for TSR firms. ***, **, *, indicate significance at the 1 %, 5 %, and 10 % level respectively. Results for *Default* in 2017–18 are not calculated because of no increase in the number of default cases for both groups.

[a] ATE for *Size* is in million yen.

impact of negative incentives set by an inadequately designed feed-in-tariffs scheme.

Funding

This study is financially supported by Nomura School of Advanced Management and the JSPS KAKENHI Grant Numbers JP16H02027J and 20H01517.

CRediT authorship contribution statement

Anna L. Sobiech: Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Hirofumi Uchida:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

None.

Acknowledgments

This study is based on a confidential policy evaluation report (original in Japanese) to the Japan Finance Corporation (JFC) written by Hirofumi Uchida, in his role as a member of the research project "Research on the Role of Policy Finance," at the Small and Medium Enterprise Unit of the Japan Finance Corporation. The authors thank the

JFC for the provision of data and various information. This study is also conducted as a part of the Project "Study group on corporate finance and firm dynamics" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). For confidentiality reasons, the authorship of Anna Sobiech did not involve the handling and processing of JFC data. An earlier version of this paper has been presented at the Spring meeting of the Japan Society of Monetary Economics, Applied Economics Workshop at Keio University, RIETI, the Sixth International Conference on Corporate Finance (University of South Carolina/Hitotsubashi University), and the RIETI DP seminar. The authors thank the two anonymous referees and the editor Richard Tol, the participants to the above workshops/seminars, Iichiro Uesugi, John Wilson, Bert Scholtens, Kozo Kiyota, Shigenori Shiratsuka, Tadanobu Nemoto, Takeo Hoshi, Yoshiyuki Arata, Kaoru Hosono, Kazuhiko Ohashi, Nobuyoshi Yamori, Hiroshi Ohashi, Masayuki Morikawa, and Ken-ichi Yoshida for their comments, Iichiro Uesugi and Hiromichi Iwaki for providing integrated data, and Kei Takahashi and Masahiro Odaka for their research support.

Appendix A

Table A1
Variable definitions.

Variable name	Definition	Comment
Rating	JFC's internal credit rating of the borrower in period *t* used for loan granting decision and determining loan terms.	A lower value indicates a lower rating, while a higher value indicates a higher rating.
Loan ratio	Total amount of short- and long-term debt divided by total assets in period *t-1*.	This variable captures borrowers' indebtedness
ROA	The return on assets using operating income in period *t-1*.	This variable reflects borrower profitability and is an indicator for capacity to service debt.
Tangibility	The amount of tangible fixed assets divided by total assets in period *t-1*.	This indicator serves as a proxy for the level of collateral that a borrower can provide to secure a loan.
Size	The natural logarithm of total assets in period *t-1*.	This variable reflects the likelihood of a firm going bankrupt (smaller firms are more likely to do so than large firms).
Sales Growth	Year-over-year sales growth rate in period *t-1*.	This variable captures firms' growth potential
Age	Borrower age calculated as the difference between the year of establishment and the year of the data entry.[a]	
Relation	Duration (year) of a lender-borrower relationship defined as the difference (in years) between the year in which the first loan from JFC was used by firm *i* and the year in which the said loan was used. (Due to the data availability on first loans, the maximum value for this variable is 22).	This variable proxies for the length of a firm's relationship with the JFC
Default	A dummy which is equal to one if a firm is bankrupt and zero otherwise (based on Rating) in period *t-1*.	
Deficit	A dummy variable which is equal to one if firm has negative operating income and zero otherwise (based on Rating) in period *t-1*.	

This table provides the definitions of variables used in the analysis.
[a] We remove observations with a calculated firm age greater than 1000 from the sample. For values of zero, we add one when taking the logarithm.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108256.

Data availability statement

The data was provided by the Japan Finance Corporation and is confidential in nature. For legal reasons, the underlying dataset used in this study is not publicly available

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