How does green credit policy affect polluting firms' dividend policy? The China experience

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ABSTRACT

We explore how polluting firms alter their dividend policy in response to pressure from green credit policy. The green credit guidelines that China adopted in 2012 aim to promote credit supply in sustainable development. Meanwhile, this green credit policy forced polluting firms to access restricted credit supply and tightened bank monitoring. Using the adoption of the green credit policy as a quasi-natural experiment, we find that polluting firms tend to lower their dividend payments, consistent with the view that dividends act as an effective tool of liquidity management and a substitute to mitigate agency problems. This finding is more pronounced among firms with weaker corporate governance, greater financial constraints, and more green innovation output. Our further analysis suggests that the green credit policy forces polluting firms to engage in less dividend smoothing.

JEL Classification: G21; G34; G35; Q55; Q58; L60

Keywords: Dividend policy; green credit policy; China; credit supply; bank monitoring; corporate governance

1. Introduction

The issues of sustainability and climate change have attracted wide attention from academia and industry. Policy makers have focused their attention on increasing financial support, from financial intermediation to sustainable projects. Several international conventions, including the Equator Principles, the United Nations Environment Programme Finance Initiative, and the International Finance Corporation Sustainability Framework, encourage banks to consider environmental factors in the credit issuance process. Beyond the unprecedented breakthrough in environmentally friendly business during the last decade, an open question remains of whether polluting and energy-intensive firms tend to adjust their financial policies under banks' environmental lending policy.

This study examines whether and how China's green credit policy influences polluting firms' dividend distribution. In 2012, the China Banking Regulatory Commission enacted green credit guidelines aimed at promoting green credit from a strategic perspective and increasing support for a green economy. As an essential component of China's national strategy for constructing an ecological civilization, the green credit policy is seen as a milestone in sustainable development in China.[2] Comprising seven chapters on green credit development, such as organization structure, lending process management, internal management, and information disclosure, the green credit policy requires commercial banks to provide more financial support to environmentally friendly enterprises and projects.

This policy requires commercial banks to assess the environmental and social risks of borrowing firms in the lending process. Article 17 of Chapter 4 states that commercial banks shall limit credit provision to a firm that fails to comply with environmental rules. Further, the

[2] It is worth noting that the Chinese government introduced a green credit policy for the first time in 2007. However, this policy was not well implemented due to pressure from economic growth and a lack of details on implementation standards, compared with the new policy enacted in 2012.

green credit policy requires commercial banks to strengthen the monitoring of borrowing enterprises with environmental and social risks, since Article 21 of Chapter 4 states that banks shall develop and implement specific post-loan management measures for borrowing firms with environmental and social risks. Thus, we argue that the adoption of the green credit policy can act as an ideal natural experiment, given that it exogenously imposes both adverse bank credit supply and strengthened the mechanisms of banks' monitoring of polluting firms.

We postulate that, after the passage of the green credit policy, the reduced credit supply and tightened bank monitoring could have decreased polluting firms' dividend payouts. First, the green credit policy causes an adverse shock of the supply of credit, which may negatively impact corporate dividend payouts. The research shows that reduced credit supply may force borrowers to scale down their business activities (Chava & Purnanandam, 2011; Alfaro et al., 2021). For example, Chava and Purnanandam (2011) suggest that negative bank credit shocks cause firms to suffer great valuation losses and declines in their capital expenditure and profitability. Alfaro et al. (2021) document that credit supply shocks have sizable and direct impacts on corporate employment and investment. Corporate dividend payouts are more sensitive to current earnings when firms rely heavily on bank debt (Aivazian et al., 2006). Thus, to the extent that earnings are the primary determinant of the volume of dividends (Lintner, 1956; Guay & Harford, 2000), polluting firms are prone to manage liquidity needs by shrinking their dividend payouts in response to the narrowed bank credit supply after the green credit policy implementation.

Further, the role of dividend payouts in mitigating agency problems may be countervailed by more stringent bank monitoring mechanisms. The traditional literature on agency theory suggests that managers may pursue excessive salaries, empire building, and other private benefits instead of maximizing the value of shareholders, whereas paying dividends could reduce free cash flows under managerial control and thus alleviate agency problems to a certain extent (Jensen & Meckling, 1976; Easterbrook, 1984). In addition, debtholders facing downside credit risk and a capped upside payoff are incentivized to alleviate moral hazard by curbing borrowers' opportunistic activities that may negatively impact their solvency (Diamond, 1991; Rajan & Winton, 1995). For example, lenders may require borrowers to provide information about their financial status on a regular basis, to evaluate their creditworthiness (Graham et al., 2008). To the extent that bank monitoring and dividends are substitutes for mitigating agency problems (Goergen et al., 2005), the incremental benefits of dividend payouts in terms of mitigating agency issues are counteracted by lenders' tightened monitoring. In addition, Allen et al. (2012) document that banks may escalate monitoring by specifying restricted borrowers' dividend payouts in the loan contract terms. Thus, we conjecture that polluting borrowers are likely to pay fewer dividends when facing strengthened monitoring from their bank lenders.

However, we could not rule out the opposite side of the above prediction, that is, the negative bank credit supply shock might not be associated with increased dividend payouts. Prior studies suggest that, when facing a reduced supply of bank capital, firms that regularly access public bond markets experience lesser declines in investment, dividend payouts, and output than those that rely primarily on bank capital (Aivazian et al., 2006; Lemmon & Roberts, 2010), weakening the expected negative association between bank credit supply and dividends. Further, signal theory suggests that paying dividends is an effective signal that indicates the firm's positive future prospects (John & Williams, 1985; Miller & Rock, 1985). Firms may maintain or even raise dividend payouts to convey positive signals to stakeholders. This argument might especially fit in our context, because the implementation of the green credit policy may impose a credit shock not only on polluting firms but also on stakeholders' concerns about their future prospects. Thus, polluting firms might be reluctant to cut dividend payouts for the purpose of preserving market perceptions when the bank credit supply is reduced due to the green credit policy.

Therefore, the impact of the green credit policy on polluting firms' dividend payouts is ultimately an open empirical question. To test the above-mentioned competing hypotheses, we conduct a difference-in-differences (DID) analysis using a sample of Chinese listed companies over the period 2007 to 2017. Our results show that the green credit policy has a negative effect on the dividend payouts of polluting firms. This effect is both statistically significant and economically sizable. Polluting firms reduced their dividend payouts by 15.38% after the adoption of the green credit policy. These results are consistent with the view that polluting firms lowered their dividend payouts in response to the constrained bank credit supply and strengthened bank monitoring following the implementation of the green credit policy.

We conduct a battery of robustness tests to strengthen our statistical inference. Our results on the dynamics of dividend policy surrounding the green credit policy's passage show no evidence of pre-treatment trends or reverse causality, and the decrease in the dividend payouts of polluting firms arises only after the implementation of the green credit policy. Another potential explanation for our results is that an omitted variable coinciding with the green credit policy's implementation could have incurred changes in polluting firms' dividend policy. To address this concern, we conduct placebo tests by randomly selecting the year when the green credit policy is adopted and control industries. We find that a falsely assumed year of green credit policy passage and pseudo-samples of treated and control firms show no effect on dividend policy. Next, our main results remain robust to propensity score matching (PSM) analysis and other robustness checks, such as alternative samples and measures of dividend payout. Overall, these analyses provide robust support for a causal interpretation of the negative effect of the green credit policy on the dividend payouts of polluting firms.

Next, we conduct several cross-sectional tests to investigate whether the effect of the green credit policy on dividend policy is affected by financial constraints, corporate governance, or green innovation. Given that the role of dividend payouts in alleviating agency problems can be countervailed by enhanced bank monitoring, we expect the effect of the green credit policy on dividend payouts to be more pronounced for firms with weaker corporate governance and more serious agency problems. In addition, green innovation investment and costly external financing may force polluting firms to preserve liquidity and lower their dividend payments, leading to the prediction that the effect of the green credit policy on dividend payouts should be stronger for firms with greater green innovation and financial constraints.

Further, to verify the efficacy of the green credit policy, we investigate whether banks reduced polluting firms' credit supply after the implementation of the policy. The empirical findings suggest that banks reduced their loan provisions to polluting companies, especially long-term loans. The increased proportion of short-term loans for polluting companies indicates that banks tend to shorten loan maturities to strengthen renegotiation frequency and monitoring mechanisms. We also investigate the impact of the green credit policy on the internal and external financing of firms. The main motivation for us to investigate firms' internal and external financing is that they are crucial in determining firms' cash dividend policies. Firms with better access to internal financing have greater flexibility in formulating their dividend policies. However, firms with a great amount of internal financing resources, such as cash holdings, may encounter severe agency problems due to the potential misuse of internal resources by managers to pursue their personal benefits. This can lead investors to demand higher dividend payouts to protect their own interests. Additionally, according to the residual dividend policy theory (Alli, Khan, & Ramirez, 1993), firms with higher external financial costs tend to adopt conservative dividend policies. Thus, given that internal and external financing are crucial factors in determining firms' dividend policies, we examine whether the green credit policy will affect polluting firms' internal and external financing policies. The results show that polluting firms reserve more cash holdings and increase supplier financing to address the pressure of the reduced bank credit supply due to the green credit policy.

Finally, we investigate how the green credit policy affects polluting firms' dividend-smoothing behavior. Provided the aforementioned signaling view is valid, polluting firms are expected to maintain or even increase their dividend distribution, to convey a positive signal to investors. Consequently, we should observe their dividend adjustment deviating from optimal levels in response to reduced bank credit supply and enhanced bank monitoring. We estimate the impact of the green credit policy on polluting firms' speed of dividend adjustment. The results provide supportive evidence on dividend-smoothing behavior consistent with previous studies (Lintner, 1956; Fama & French, 2002; Aivazian et al., 2006). Moreover, we find that polluting firms smooth their dividends significantly less after the adoption of the green credit policy.

This paper makes several contributions. First, it adds to the literature on the microeconomic consequences of climate change regulations. Prior environmental economic studies document that emission abatement policies affect firm productivity, employment, accounting, and stock market performance (Anger & Oberndorfer, 2008; Veith et al., 2009; Commins et al., 2011; Bushnell et al., 2013; Oestreich & Tsiakas, 2015; Dardati & Riutort, 2016; Kang & Létourneau, 2016; Marin et al., 2018). A number of studies investigate how climate policy impact corporate financing activities. Seltzer et al. (2022) show that after the Paris Agreement firms may have lower credit ratings due to a poor environmental image or a high carbon footprint. Dang et al. (2020) show that the NOx Budget Trading Program of 2004 forces manufacturing firms to reduce their financial leverage. Prior studies on China's green credit policy of 2012 investigate its impacts on environmental quality (Zhang et al., 2021), green innovation (Hu et al., 2021), and operational performance (Yao et al., 2021). However, few studies examine whether and how climate change policy could influence corporate dividend decisions. Our research fills the gap by showing that the green credit policy that is set to boost clean production and a sustainable environment propels firms with problematic environmental profiles to taper their dividend distribution.

Second, this paper contributes to the literature on bank environmental lending. Thompson and Cowton (2004) suggest that, with increasing public concern about the natural environment, banks tend to demand environmental information and estimate the environmental implications when making their lending decisions. Delis et al. (2019) document similar findings after the Paris Agreement of 2015. Jung et al. (2018) find that lenders incorporate borrowers' exposure to carbon-related risk into lending decisions through the cost of financing. Our study extends this stream of literature by investigating the green credit policy in China, which requires banks to conduct strict environmental scrutiny over borrowers. We provide evidence that the mandated inspection of environmental information impacts both bank lending decisions and polluting borrowers' dividend payments.

Third, we provide novel evidence on the causal impact of banks' credit supply and monitoring mechanisms on borrowers' dividend payouts. The literature on dividend policy separately documents that credit supply shocks would decrease firms' dividend payout ratios (Campello et al., 2010; Dwenger et al., 2020) and that bank monitoring may reduce the value of agency reduction roles initially fulfilled by dividend payouts, thereby reducing borrowers' dividend payouts (Goergen et al., 2005; Aivazian et al., 2006; Allen et al., 2012). This study sheds new light on how an exogenous shock that reduces credit supply but at the same time strengthens bank monitoring affects corporate payout decisions. Our finding that polluting firms narrow their dividend levels in response to pressure from the green credit policy contributes to supporting the causal relation between credit supply, bank monitoring, and corporate dividend policy.

Lastly, this study adds to the literature on corporate governance regulations in China. Papers in this strand include those of Chen et al. (2018), He and Wang (2022), Hou et al. (2012), Jiang and Kim (2015, 2020), Liao et al. (2014), and Qian and Chen (2021). In relation to this literature, instead of mandatory corporate social responsibility disclosure (Chen et al., 2018) or the split-share structure reform (Hou et al., 2012; Liao et al., 2014), we examine environmental externality–related regulation in China and study its real effects on polluting firms' dividend policy. Further, the green credit policy in our study reinforces the monitoring role of bank lenders in China, extending corporate governance research on China (Jiang & Kim, 2015, 2020).

The remainder of this paper is organized as follows. In Section 2, we present the data and methodology. Section 3 reports our main empirical results. In Section 4, we discuss the results from cross-sectional tests. We conduct additional analysis in Section 5 and verify the validity of the green credit policy in Section 6. Finally, Section 7 concludes the paper.

2. Data and methodology

2.1. Sample selection

Our sample covers firms listed on the Shanghai Stock Exchange or the Shenzhen Stock Exchange from 2007 to 2017, five years before and five years after the beginning of the green credit policy. We obtain stock return, dividend payout, and other financial accounting data from the China Stock Market & Accounting Research Database. In addition, we obtain green innovation data from Chinese Research Data Services. By combining these databases, we obtain our main sample, which consists of 22,492 firm–year observations from 2,788 unique firms. We winsorize continuous variables at the top and bottom 1% to mitigate the effects of outliers.

2.2. Empirical methods

We use the following standard difference-in-differences (DID) regression framework:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} + \beta_2 PLT_{i,t} \times Post_t + \beta_3 Post_t + \delta' \times Controls_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $Dividend_{i,t}$ is the dividend payout normalized by firm *i*'s total assets at the end of year *t* (Ye et al., 2019; Hasan & Uddin, 2022). In robustness checks, we employ alternative measurements of dividend payout to re-estimate the relation between green credit policy and dividend payouts. The variable *PLT* is an indicator equal to one if a firm is in a polluting industry, and zero otherwise,[3] and *Post* is an indicator set to one for 2012 and later, and zero otherwise. $Controls_{i,t}$ is a vector of control variables. The coefficient of key interest is β_2, associated with the interaction term $PLT_{i,t} \times Post_t$, which captures the differential change in cash dividends post-policy implementation between polluting and non-polluting firms.

Following prior dividend payout literature (Firth et al., 2016; Jiang et al., 2017; Ye et al., 2019; Hasan & Uddin, 2022), we include a set of control variables that have been identified to potentially affect dividend payouts. These variables include firm size (*SIZE*), financial leverage (*LEV*), the return on assets (*ROA*), cash holdings (*CASH*), the market-to-book ratio (*MTB*), stock return volatility (*VOL*), and ownership concentration (*OWNCON*). We also include year, industry, and firm fixed effects in our regression model. The year fixed effects

[3] In 2008, the Chinese Ministry of Environmental Protection promulgated the "Directory of Environmental Verification and Industry Category Management of Listed Corporations," which stipulates which industries are polluting industries. According to this directory, we classify the following 16 industries as polluting industries: the coal mining and washing industry; ferrous metal mining; non-ferrous metal mining; non-metallic mining; wine, beverage, and refined tea manufacturing; textiles, paper, and paper products; petroleum processing; the coking and nuclear fuel processing industry; chemical raw materials and chemical products manufacturing; pharmaceutical manufacturing; chemical fiber manufacturing; the non-metallic mineral products industry; the ferrous metal smelting and rolling processing industry; the non-ferrous metal smelting and rolling processing industry; the rolling processing industry; the electricity and heat production and supply industry; and the gas production and supply industry.

account for national economic conditions, while the industry and firm fixed effects help to mitigate omitted time-invariant industry- and firm-level factors, respectively, that affect dividend payouts.

3. Empirical results

3.1. Descriptive statistics

Panel A of Table 1 presents the summary statistics of the variables used in our main regressions. We observe that the average value of *Dividend* is 0.013, which is consistent with that reported by Firth et al. (2016). This suggests that, on average, a typical firm in our sample pays out 1.3% of its total assets as dividends, which is close to the firms in countries studied by Bae et al. (2012). The mean value of *PLT* is 0.318, which suggests that approximately one-third of Chinese listed firms are polluting firms. The summary statistics of other variables are largely consistent with prior studies (Firth et al., 2016; Jiang et al., 2017; Ye et al., 2019; Hasan & Uddin, 2022).[4]

Panel B of Table 1 presents the Pearson correlations among the variables used in our main regressions. We observe that *Dividend* is positively correlated with *Post*, which means companies tend to pay more dividend payouts after 2012. The variable *Dividend* is also positively correlated with firm size (*SIZE*), the return on assets (*ROA*), cash holdings (*CASH*), the market-to-book ratio (*MTB*), and ownership concentration (*OWNCON*) and negatively correlated with financial leverage (*LEV*) and stock return volatility (*VOL*), consistent with the work of Jiang et al. (2017).

[4] The mean value of cash holding ratio (CASH) is 16.3%, which is higher than that reported for firms in the countries studied by Kalcheva and Lins (2007), indicating that Chinese firms tend to hoard a substantial amount of cash. Moreover, the mean debt-to-asset ratio (LEV) is 47.7% which is lower than the average value reported for G-7 countries in the study conducted by Mahajan and Tartaroglu (2008). In addition, we observe that the mean of VOL, representing the standard deviation of daily stock returns over the year, is 3.3%.

[Insert Table 1 about here]

3.2. Baseline results

Our baseline regression model captures the impact of the implementation of the green credit policy on firms' dividend payouts. Specifically, we employ the following model:

$$\begin{aligned} Dividend_{i,t} = \alpha &+ \beta_1 PLT_{i,t} + \beta_2 PLT_{i,t} \times Post_t + \beta_3 Post_t + \beta_4 SIZE_{i,t} + \beta_5 LEV_{i,t} \\ &+ \beta_6 ROA_{i,t} + \beta_7 CASH_{i,t} + \beta_8 MTB_{i,t} + \beta_9 VOL_{i,t} + \beta_{10} OWNCON_{i,t} \\ &+ Year_t + Industry_j + Firm_i + \varepsilon_{i,t} \end{aligned} \quad (2)$$

Table 2 presents the baseline regression results. In column (1), we regress the dividend payout measure, *Dividend,* on *PLT*, *PLT* × *Post*, and *Post* with all firm-level control variables but without year or industry fixed effects. In column (2), we add year and industry fixed effects. To address the concern that our results may be affected by firm heterogeneity, in column (3) we include firm fixed effects to account for firm-level heterogeneity.

The results in column (1) show that the coefficient on *PLT* is significantly positive (*t*-value=2.71), indicating that polluting firms tend to pay higher cash dividends than non-polluting firms. One possible explanation for this phenomenon is that the majority of polluting firms are in the mature stage of their life cycle and more capable of distributing cash dividends to their shareholders. On the other hand, the results show that the coefficient on *Post* is significantly positive (t-value=2.15), indicating an increase in dividend payout during the sample period. The coefficients on *PLT* × *Post* are significantly negative (*t*-value = -3.04 in column (1), -2.85 in column (2), and -2.75 in column (3)), suggesting that the green credit policy contributes to the reduction of polluting firms' dividend payouts, in line with the above hypothesis that the implementation of the green credit policy induced polluting firms to reduce dividend payouts.

The impact of the implementation of the green credit policy on firms' dividend payouts is also economically meaningful. The coefficients on *PLT* × *Post* in columns (1) to (3) of Table 2 show that, with all other factors held the same, *Dividend* decreases by approximately 0.002 after the implementation of the green credit policy. Given that the sample mean value of *Dividend* is 0.013, we can conclude that the green credit policy led to a 15.38% reduction in the dividend payouts of polluting companies. Overall, the negative association between the green credit policy and dividend payouts is not only statistically significant, but also economically meaningful.

The results show that the coefficients on financial leverage (*LEV*) are significantly negative, in line with the results of Jensen et al. (1992), indicating that highly leveraged firms tend to pay fewer dividend payouts. We also find that the coefficients on ownership concentration (*OWNCON*) are significantly positively, consistent with the work of Firth et al. (2016), suggesting that a higher concentration of large shareholders would enable these shareholders to better monitor management activities and increase dividend payouts. Moreover, the signs of the coefficients on the remaining control variables, such as firm size (*SIZE*), the return on assets (*ROA*), cash holdings (*CASH*), the market-to-book ratio (*MTB*), and stock return volatility (*VOL*), are consistent with prior literature (Desai & Jin, 2011; Balachandran & Nguyen, 2018; Hasan & Uddin, 2022).

[Insert Table 2 about here]

3.3. Endogeneity concerns and robustness checks

3.3.1. Pre-treatment trends analysis and placebo tests

The key identifying assumption behind the DID method is the parallel trends assumption, which assumes that the outcome variable displays similar trends in the treatment and control groups during the pre-shock period. In this study, the parallel-trends assumption requires similar trends in dividend payout levels for polluting and non-polluting firms before the implementation of the green credit policy. The DID estimates can plausibly isolate the effects of the policy if the parallel-trends assumption holds. To verify this assumption, following the method of Bertrand and Mullainathan (2003), we examine the dynamic effects of the green credit policy on dividend payouts.

We use two specifications to examine whether firms in polluting industries and those in non-polluting industries satisfy the parallel pre-treatment trends assumption. First, following Dang et al. (2022), we construct five dummy variables surrounding the green credit policy: $Before^{3+}$, $Before^{1,2}$, $After^{0}$, $After^{1,2}$, and $After^{3+}$, where $Before^{3+}$ equals one for the period three or more years prior to the green credit policy (except the sample start year 2007), $Before^{1,2}$ equals one for the one or two years prior to the green credit policy, $After^{0}$ equals one for the year of green credit policy, $After^{1,2}$ equals one for the one or two years after the green credit policy, and $After^{3+}$ equals one for the period three or more years after the green credit policy. Specifically, we employ the following model:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Before_t^{3+} + \beta_2 PLT_{i,t} \times Before_t^{1,2} + \beta_3 PLT_{i,t} \times After_t^{0} + \beta_4 PLT_{i,t} \times After_t^{1,2} + \beta_5 PLT_{i,t} \times After_t^{3+} + \delta' \times Controls_{i,t} + \varepsilon_{i,t} \quad (3)$$

We present the estimation results in Panel A of Table 3. In column (1), we regress the dividend payout measure, Dividend, on these five dummy variables without firm-level control variables, but with year and firm fixed effects. In column (2), we further add firm-level control variables. The results show that the coefficients on PLT × Before3+ and PLT × Before1,2 are statistically insignificant, indicating no significant change in dividend payouts prior to the green credit policy. The coefficients on PLT × After0, PLT × After1,2, and PLT ×After3+ are significantly negative, in line with the main findings.

[Insert Table 3 about here]

Next, following Beck et al. (2010), we graphically test the year-to-year impact of the green credit policy on dividend payouts around the implementation year. We replace the dummy variable *Post* in Eq. (1) with eight dummy variables, namely, $Before^4$, $Before^3$, $Before^2$, $Before^1$, $After^1$, $After^2$, $After^3$, and $After^4$, to examine the dynamic effects of the green credit policy, where $Before^4$ is set to one for the period four years before the green credit policy, $Before^3$ is set to one for the three years before the green credit policy, $Before^2$ is set to one for the two years before the green credit policy, $Before^1$ is set to one for the one year before the green credit policy, $After^1$ is set to one for the one year after the green credit policy, $After^2$ is set to one for the two years after the green credit policy, $After^3$ is set to one for the three years after the green credit policy, and $After^4$ is set to one for the period four years after the green credit policy. Specifically, we employ the following model:

$$\begin{aligned} Dividend_{i,t} = {} & \alpha + \beta_1 PLT_{i,t} \times Before_t^4 + \beta_2 PLT_{i,t} \times Before_t^3 + \beta_3 PLT_{i,t} \times Before_t^2 \\ & + \beta_4 PLT_{i,t} \times Before_t^1 + \beta_5 PLT_{i,t} \times After_t^1 + \beta_6 PLT_{i,t} \times After_t^2 \\ & + \beta_7 PLT_{i,t} \times After_t^3 + \beta_8 PLT_{i,t} \times After_t^4 + \delta' \times Controls_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (4)$$

Figure 1 shows the results. As shown in Fig. 1, we plot the coefficients on those dummy variables and the corresponding 95% confidence intervals. Again, the coefficients on the pre-policy indicators $Before^4$, $Before^3$, $Before^2$, and $Before^1$ are statistically nonsignificant, suggesting no pre-treatment trends. Overall, none of these results shows evidence of pre-treatment trends or reverse causality in firms' dividend policy.

[Insert Fig 1 about here]

Although we demonstrated above that our results hold when controlling for time-varying control variables, as well as year and firm fixed effects, concern might remain about the possibility of our results being driven by other, unobserved shocks. To address this concern, we employ two placebo tests. First, following Chen et al. (2018), we shift the event year by two years before the actual event year and define a placebo indicator, *Post_Pseudo*, which is set to one after the pseudo-event-year (2010), and zero otherwise. Column (1) of Panel A of Table 3 shows that the coefficient on *PLT* × *Post_Pseudo* is nonsignificant, indicating no relation between the green credit policy and dividend payouts during the pseudo-shock period.

Second, following Dang et al. (2020), we use firms from randomly selected control industries as the pseudo-treated group and firms from the remaining control industries as the control group. We define *PLT_Pseudo* as set to one if a firm is in a randomly assigned polluting industry, and zero otherwise. Column (2) of Panel A of Table 3 shows that the coefficient on *PLT_Pseudo* × *Post* is nonsignificant, suggesting our main findings are unlikely to be driven by unobserved common shocks in 2012. Overall, the results of the placebo tests provide further support to our baseline findings.

3.3.2. PSM-DID analysis

To address the concern that differences in firm characteristics between the treatment group and the control group may be driving differences in dividend payouts, following DeFond et al. (2015), we use a PSM strategy to identify the regression sample. First, we retain only observations in 2011, the year prior to the green credit policy. Then, we use a logit model to estimate the propensity score of being a treated firm. We include all control variables specified in our baseline model. Next, according to their propensity scores, we match treatment to control firms using the one-to-one nearest neighbor matching method without replacement. To ensure the characteristics between the treatment group and control group have no significant differences, we use a caliper width of 0.005. In the end, we obtain 430 pairs of treated and control firms.

Panel A of Table 4 presents the univariate comparisons of firm characteristics between these two groups. Columns (1) and (2) report the mean values of the firm characteristics, and column (3) reports the *t*-statistics of the univariate comparisons between these two groups. The results show that all *t*-statistics are nonsignificant, suggesting the covariate balance condition has been satisfied. Then we re-estimate Eq. (1) using the PSM sample, and the results are shown in Panel B. In column (1), we regress *Dividend* on all firm-level control variables with year and industry fixed effects. In column (2), we regress *Dividend* on all firm-level control variables with year and firm fixed effects. We find that the coefficients on *PLT* × *Post* are significantly negative, in line with our baseline findings. Overall, the results from the PSM identification method further support our baseline findings.

[Insert Table 4 about here]

3.3.3. Robustness tests

We conduct a set of robustness tests and report the results in Table 5. In Panel A, we rerun the baseline specification using various subsamples. First, in column (1), we restrict our test window to three years before and three years after the year of green credit policy. Second, in column (2), following Dang et al. (2020), we exclude observations in the adoption year, 2012. Then, in column (3), we remove firms that changed their industrial classification during the sample period (2007–2017). Next, we use subsamples free of non-dividend payers and report the results in column (4). In the last column, we impose a stricter condition that requires firms to maintain dividend payments during the sample period (2007–2017). The results of all the columns across Panel A are largely consistent with our main findings.

Further, in Panel B of Table 5, we examine whether our results are robust to alternative measures of dividend payout. Following prior studies (e.g., Desai & Jin, 2011; Jiang et al., 2017; Balachandran & Nguyen, 2018; Ye et al., 2019; Hasan & Uddin, 2022), we define 1) *DIV1* as the total amount of dividend payouts by net earnings, 2) *DIV2* as the ratio of dividends to the market value of equity, 3) *DIV3* as the dividend payout subtracted from the mean dividend payout of all firms within the same province, normalized by total assets, and

4) *DIV_DUM* as one if a firm provides dividend payouts, and zero otherwise. As shown in Panel B, the estimation results based on these alternative measures are still in line with the main findings.

[Insert Table 5 about here]

4. Cross-sectional tests

4.1. The role of financial constraints

So far, our findings suggest that the negative effect of the green credit policy on dividend payouts is driven by reduced bank credit supply. To provide further evidence, we perform cross-sectional tests based on the strength of firms' financial constraints. To the extent that firms with tight financial constraints tend to reduce dividend payouts (DeAngelo and DeAngelo (1990), we expect that the decline in dividend payout should be more pronounced in firms with tighter financial constraints.

To test the above conjecture, we follow previous studies and use three proxies of financial constraint. The first proxy is the Kaplan–Zingales (1997) index, which measures the degree of external financing reliance. When financial conditions tighten, companies with higher KZ index scores are more likely to encounter difficulties. The second proxy is the Whited–Wu (2006) index. In contrast to the commonly used KZ index, the WW index emphasizes the characteristics of firms that are influenced by external financial constraints. The third proxy for financial constraint, the SA index, is drawn from Hadlock and Pierce (2010) and is based solely on firm size and age. According to Hadlock and Pierce (2010), firm size and age predict financial constraint levels particularly well. We classify a firm as financially constrained if its proxy for financial constraint is above the sample median.

In columns (1) to (3) of Table 6, we employ DDD models that use the aforementioned three proxies for financial constraints. For all three measures, financially constrained firms are more affected by the green credit policy, whereas the effect of the policy is never significant in unconstrained firms. The difference between financially constrained and unconstrained firms is -0.3% when financial constraints are measured by the KZ index. The difference between financially constrained and unconstrained firms is -0.2% when financial constraints are measured by the WW index. The difference between financially constrained and unconstrained firms is -0.3% when financial constraints are measured by the SA index. These results support the conjecture that the decline in dividend payout following the green credit policy is driven by the reduced credit supply.

[Insert Table 6 about here]

4.2. The role of corporate governance

Our previous discussion and analysis suggest that the negative effect of the green credit policy on dividend payouts is driven by enhanced bank monitoring. To provide more direct evidence on this mechanism, we perform cross-sectional tests based on the strength of corporate governance. We expect the effect of the green credit policy on dividend payouts to be more pronounced for firms with weaker corporate governance, for which bank monitoring plays a more prominent role. In weakly governed firms, agency problems are more serious, and enhanced bank monitoring could alleviate these agency problems, which are initially mitigated by dividend payout. Thus, such firms will lower their dividend payouts more once their lending banks enhance monitoring.

According to previous research, we use four corporate governance proxies to test this prediction. The first is analyst coverage, which we measure as the number of analysts or analyst teams who follow the company during the year. As shown by Chen et al. (2015), analysts can reduce corporate agency problems by scrutinizing management behaviors. We set an indicator variable *ANALYST* to one if the number of analysts or analyst teams following a firm is below the sample median. The second governance proxy, analysts' site visits, is calculated as the number of analysts or analyst teams who visited the company during the year, given that analysts can reduce information asymmetry and monitor management behavior by conducting site visits (Su et al., 2021). We define a dummy variable *VISIT* to one if the number of analyst visits to a firm is below the median. The third proxy for corporate governance is total institutional ownership, which is the sum of the shareholdings of all institutional investors. Chung and Zhang (2011) show that institutional investors hold a higher percentage of shares when a company has good corporate governance. We set an indicator *INSOWN* to one if the institutional investor shareholdings in a firm is below the median ratio. The fourth proxy for corporate governance is *SOE*, an indicator variable that is equal to one if a firm is a state-owned enterprise. The information transparency of state-owned enterprises is low, and they may pursue political objectives rather than value maximization (Bai et al., 2006; Jiang & Kim, 2020). Thus, the corporate governance of state-owned enterprises is relatively weak.

We employ difference-in-difference-in-differences (DDD) models using each of the corporate governance dummies constructed above. The results are reported in Table 7. The coefficients on the triple interaction term between *PLT* × *Post* and each of the corporate governance dummies are all negative and statistically significant. Hence, after the green credit policy, dividend payouts in polluting firms with weak corporate governance decline more than in firms with strong corporate governance. These findings support the bank monitoring mechanism.

[Insert Table 7 about here]

4.3. The role of green innovation

In this section, we investigate the impact of green innovation on the relation between the green credit policy and a corporate dividend policy. We test whether polluting firms with greater green innovation are more affected by the green credit policy. Although banks' environmental lending would encourage polluting firms to invest more in green innovation, the increased green innovation investment may squeeze the free cash that could initially be distributed in the form of dividends. So, the effect of the green credit policy on dividend payouts should be stronger in firms with greater green innovation.

To test this prediction, we use three proxies for green innovation. The first is the number of green patent applications. Specifically, it is calculated as the sum of the number of green invention patent applications and the number of green utility model patent applications. The second and third proxies are calculated similarly and are based on green patent gains and green patent citations, respectively. We classify a firm as green innovative if its green innovation proxy is above the sample mean.

In Table 8, columns (1) to (3), we employ DDD models using each of the three dummies based on the above-mentioned three proxies for green innovation. In column (1), the coefficient on *PLT* × *Post* × *INNO_APP* is negative and statistically significant. This result indicates that firms with more green patent applications are more affected by the green credit policy. We can find similar figures in columns (2) and (3) when we use green patent gains and green patent citations as proxies for green innovation. These results lend support to the bank monitoring mechanism.

[Insert Table 8 about here]

5. How effective is the green credit policy?

In this section, we examine whether the implementation of the green credit policy could affect polluting firms' liquidity and financing policies. We are motivated to verify the efficacy of the green credit policy and explore how firms adjust their cash holdings and seek funds from sources other than their banks in response to the credit pressure of the green credit policy.

5.1. Bank lending

First, we examine whether banks reduce their loans to polluting firms, as well as whether these banks would enhance the monitoring of these polluting firms after the adoption of the green credit policy. The green credit policy aims to promote credit supply in sustainable development. Meanwhile, this policy is intended to reduce the credit supply and tighten the bank monitoring of polluting firms. Consequently, we expect a decrease in bank loans to polluting firms and an increase in the bank monitoring of these firms after the implementation of the green credit policy.

We employ DID models to test these predictions. According to (Rajan & Winton, 1995; Gustafson et al., 2021), we employ a short-term bank ratio as a proxy for bank monitoring. The control variables are consistent with prior studies (e.g., Bae & Goyal, 2009), including *SIZE*, *AGE*, *ROA*, *LEV*, *B_SIZE*, and *B_IND*.

Panel A of Table 9 reports the regression results. The coefficients on *PLT* × *Post* in the *Loan* and *Long Loan* regressions are negative and significant, whereas the coefficient on *PLT* × *Post* in the *Short Loan* regression is insignificant. According to these results, banks reduce loans to polluting companies, particularly long-term loans, but make few adjustments to short-term loans to polluting borrowers. These results are consistent with prior studies on green credit policy (e.g., Chang et al., 2019). Furthermore, the coefficient on *PLT* × *Post* in the *Short Loan Ratio* regression is positive and significant, indicating that banks enhance their monitoring of these polluting borrowers.

Our findings testify to the efficacy of the green credit policy in curbing the bank credit supply to polluting borrowers. In particular, it is more difficult for polluting borrowers to access long-term bank loans since the adoption of the green credit policy. Although banks barely adjust the provision of short-term loans to polluting borrowers, the increased proportion of short-term loans may reflect the enhanced bank monitoring mechanism, which is in line with our conjecture.

5.2. Liquidity and other financing decisions

We are also interested in polluting firms' ex post liquidity policy, which is closely associated with their dividend policy. If polluting firms indeed reduce their dividend payouts due to restricted access to bank credit, they are expected to preserve internally generated cash flows, which is less costly than external funding sources.

In column (1) of Panel B of Table 9, we present the regression results for cash holdings. The control variables are consistent with prior studies on cash holdings (e.g., Opler et al., 1999). The results show that the green credit policy has a significant and positive effect on polluting companies' cash holdings, which is consistent with our conjecture.

Next, we explore the impact of green credit policy on a variety of financing decisions for polluting firms, including the issuance of equity and bonds, as well as supplier financing. Studies have documented that supplier financing can substitute for bank credit (Love et al., 2007; Garcia-Appendini & Montoriol-Garriga, 2013). Thus, we expect polluting firms would increase supplier financing to alleviate the pressure caused by the decrease in bank credit supply.

Columns (2) to (4) of Panel B of Table 9 show the regression results of the green credit policy on firms' financing choices. The results show that polluting firms opt for increasing supply chain financing rather than issuing more stocks to compensate for the reduction in bank loans after the implementation of the green credit policy. Moreover, we find that polluting firms issue significantly fewer public bonds after the policy's adoption. In addition, we investigate whether the green credit policy could affect the financial leverage of polluting firms. As shown in column (5), the financial leverage of polluting firms decreases significantly after the implementation of the policy, which is in line with our previous findings; that is, the bank loans and public bonds of polluting firms decrease significantly after the adoption of the policy.

[Insert Table 9 about here]

6. Green credit policy and dividend smoothing

Lintner's (1956) seminal study documents that dividend changes respond slowly to earnings changes and managers are inclined to bear significant costs to avoid dividend reduction. Prospect theory explains the motive of dividend smoothing as investors' preference for stable dividends and consumption (Baker et al., 2007; Baker et al., 2016), while agency theory suggests that dividend smoothing may help alleviate the agency conflicts between managers and outside shareholders by exposing the firm to the discipline of investor monitoring (Easterbrook, 1984; Allen et al., 2000; Baker & Wurgler, 2004). According to the signal theory, polluting firms may smooth dividends more after the implementation of the green credit policy, as a means of conveying positive signals to the market. In contrast, according to agency theory, polluting firms may smooth less after the implementation of the green credit policy, given that the role of dividend smoothing in mitigating agency problems may be countervailed by enhanced bank monitoring. Our main findings lend support to the agency theory view, while failing to support the signal theory view. To further validate these conclusions, we investigate the dividend smoothing behavior of polluting firms. Specifically, we examine the prevalence of dividend smoothing and how such dividend-smoothing behavior could be influenced by the passage of the green credit policy.

To explore the above issues, we construct the following modified model based on a dividend-smoothing measurement used in previous studies (Lintner, 1956; Fama & French, 2002):

$$\Delta Dividend_{i,t} = \alpha + \beta_1 Dividend_{i,t-1} + \beta_2 PLT_{i,t} \times Post_t \times Dividend_{i,t-1} + \beta_3 PLT_{i,t} \times Post_t + \beta_4 ROA_{i,t} + Year_t + Industry_j + \varepsilon_{i,t} \quad (5)$$

where $Dividend_{i,t}$ is the dividend payout of firm *i* in year *t*, normalized by the total assets of firm *i* at the end of year *t*. The speed of adjustment (γ) can be estimated as $-\hat{\beta}_1$ (Leary & Michaely, 2011), while the negative of the coefficient $\hat{\beta}_2$ indicates the effect of the green credit policy on polluting firms' speed of adjustment. A positive (negative) coefficient of $\hat{\beta}_2$ suggests that the green credit policy decreases (increases) polluting firms' speed of adjustment or encourages (discourages) their dividend-smoothing activity.

The results are presented in Table 10. We find that $\hat{\beta}_1$ (the coefficient on $Dividend_{i,t-1}$) is negative and significant at the 1% level, suggesting the existence of dividend smoothing, which is in line with previous literature (Fama & French, 2002; Leary & Michaely, 2011; Lintner, 1956). Moreover, the results show that $\hat{\beta}_2$ (the coefficient on *PLT* × *Post* × $Dividend_{i,t-1}$) is negative and significant at the 5% level, indicating that polluting firms smooth dividends less after the implementation of the green credit policy. This finding is opposite to the signal theory expectation that polluting firms are inclined to smooth dividends to convey positive signals to outside investors. Our results are also consistent with the view that firms engage in less dividend smoothing when agency problems can be mitigated by enhanced bank monitoring. Overall, the analysis of dividend smoothing lends further support to our main findings.

[Insert Table 10 about here]

7. Conclusion

This study investigates whether and how the green credit policy in China influences polluting firms' dividend payouts. To test this issue, we conduct a quasi-natural experiment by utilizing the green credit policy in China as an exogenous shock to both the credit supply and bank monitoring. The empirical results show that the green credit policy has a negative effect on the dividend payouts of affected borrowing firms, which is consistent with our hypothesis that reduced credit supply and enhanced bank monitoring decrease corporate dividend payouts. This finding holds for a battery of robustness checks, including pre-treatment trends analysis, PSM analysis, placebo tests, and the use of various subsamples and alternative measures of dividend payout.

We further show that the negative effect of the green credit policy on dividend payouts is more pronounced among firms with weaker corporate governance, greater financial constraints, and more green innovation output. Our analyses on the effectiveness of the green credit policy confirm the view that polluting firms adopt more conservative financing and liquidity policies in response to the pressure from the green credit policy. Lastly, we provide additional support for our hypotheses by showing that polluting firms smooth dividends less after the adoption of the green credit policy.

Overall, this paper sheds light on the microeconomic consequences of climate change policies and banks' environmental lending. Practitioners may benefit from this study in that narrowing dividend distribution can an important firm-level consequences of the green credit policy on polluting sectors. Our findings may also have noteworthy political implications. China, as the world's second largest economy, benefits enormously from unsustainable development. Therefore, our evidence on China provides insights for policy makers from other countries that aim to enact policies on climate change and sustainability.

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Table 1. Descriptive statistics and correlation matrix

This table reports the descriptive statistics and correlation matrix of variables used in our main empirical analysis. The sample consists of 22,492 firm–year observations over the period from 2007 to 2017. For the definitions of all the variables and the details of their construction, see appendix. All the continuous variables are winsorized at the 1% and 99% levels.

Panel A. Descriptive statistics						
Variable	N	Mean	Std. Dev.	P25	Median	P75
Dividend	22,492	0.013	0.021	0.000	0.006	0.017
PLT	22,492	0.318	0.466	0.000	0.000	1.000
Post	22,492	0.618	0.486	0.000	1.000	1.000
SIZE	22,492	22.096	1.442	21.118	21.901	22.856
LEV	22,492	0.477	0.221	0.308	0.476	0.639
ROA	22,492	0.036	0.060	0.012	0.034	0.063
CASH	22,492	0.163	0.134	0.069	0.123	0.214
MTB	22,492	2.708	2.150	1.409	2.023	3.152
VOL	22,492	0.033	0.017	0.024	0.029	0.039
OWNCON	22,492	0.171	0.122	0.075	0.141	0.240

Panel B: Pearson correlation matrix

	Dividend	PLT	Post	SIZE	LEV	ROA	CASH	MTB	VOL	OWNCON
Dividend	1									
PLT	0.003	1								
Post	0.045***	-0.032***	1							
SIZE	0.196***	0.001	0.199***	1						
LEV	-0.264***	-0.014**	-0.073***	0.381***	1					
ROA	0.458***	-0.002	-0.037***	0.032***	-0.390***	1				
CASH	0.236***	-0.127***	-0.086***	-0.159***	-0.376***	0.281***	1			
MTB	0.070***	-0.009	-0.019***	-0.509***	-0.224***	0.117***	0.199***	1		
VOL	-0.010	-0.025***	-0.180***	-0.220***	-0.085***	0.040***	0.157***	0.246***	1	
OWNCON	0.200***	0.024***	-0.022***	0.256***	-0.013*	0.147***	0.036***	-0.095***	0.038***	1

Table 2. Green credit policy and corporate dividend policies

This table presents the OLS regression results of the effect of green credit policy on firms' dividend policies. We employ the following difference-in-differences model:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} + \beta_2 PLT_{i,t} \times Post_t + \beta_3 Post_t + \beta_4 SIZE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 ROA_{i,t} + \beta_7 CASH_{i,t} + \beta_8 MTB_{i,t} + \beta_9 VOL_{i,t} + \beta_{10} OWNCON_{i,t} + Year_t + Industry_j + Firm_i + \varepsilon_{i,t}$$

The sample consists of 22,492 firm–year observations from 2007 to 2017. The dependent variable *Dividend* is calculated as the dividend payout divided by total assets. For the definitions of all the variables and the details of their construction, see appendix. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Dividend	(2) Dividend	(3) Dividend
PLT	0.002***		
	(2.71)		
PLT × Post	-0.002***	-0.002***	-0.002***
	(-3.04)	(-2.85)	(-2.75)
Post	0.001**		
	(2.15)		
SIZE	0.004***	0.003***	0.001*
	(9.71)	(9.04)	(1.85)
LEV	-0.017***	-0.017***	-0.010***
	(-15.13)	(-15.43)	(-7.77)
ROA	0.115***	0.114***	0.064***
	(20.38)	(21.06)	(15.49)
CASH	0.017***	0.017***	0.016***
	(8.96)	(9.66)	(8.68)
MTB	0.000***	0.000***	0.000***
	(4.56)	(5.04)	(7.33)
VOL	-0.006***	-0.007***	-0.003
	(-3.22)	(-3.82)	(-1.55)
OWNCON	0.014***	0.018***	0.013***
	(4.84)	(7.68)	(4.01)
Constant	-0.067***	-0.045***	0.002
	(-8.74)	(-7.18)	(0.30)
Year FE	No	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes
Observations	22,492	22,492	22,492
Adjusted-R^2	0.295	0.361	0.632

Table 3. Pre-treatment trends and placebo analyses

This table presents the estimation results of the pre-treatment trends analysis and placebo test. Panel A presents the estimation results of the pre-treatment trends analysis using a dynamic specification. We employ the following model:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Before_t^{3+} + \beta_2 PLT_{i,t} \times Before_t^{1,2} + \beta_3 PLT_{i,t} \times After_t^{0} + \beta_4 PLT_{i,t} \times After_t^{1,2} + \beta_5 PLT_{i,t} \times After_t^{3+} + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

Before^{3+} is an indicator variable that takes one for observations with three years or more prior to the green credit policy, and zero otherwise. *Before*^{1,2} is an indicator variable that takes one for observations with one or two years prior to the green credit policy, and zero otherwise. *After*^{0} is an indicator variable that takes one for the year of green credit policy, and zero otherwise. *After*^{1,2} is an indicator variable that takes one for observations with one- or two-years post-policy, and zero otherwise. *After*$^{3+}$ is an indicator variable that takes one for observations with three years or more post-policy, and zero otherwise. Panel B presents the results of placebo tests. We employ the following two models:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post\_Pseudo_t + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

$$Dividend_{i,t} = \alpha + \beta_1 PLT\_Pseudo_{i,t} \times Post_t + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

Post_Pseudo is an indicator variable that is equal to one for year after the pseudo-event-year (2010), and zero otherwise. *PLT_Pseudo* is an indicator variable that is equal to one if a firm is in a randomly assigned polluting industry, and zero otherwise. For the definitions of all the variables and the details of their construction, see appendix. All models include year and firm fixed effects. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pre-treatment trends analysis

	(1) Dividend	(2) Dividend
PLT × Before^{3+}	-0.001	0.000
	(-1.12)	(0.22)
PLT × Before^{1,2}	-0.001	0.000
	(-1.41)	(0.22)
PLT × After^{0}	-0.003***	-0.001**
	(-3.33)	(-1.97)
PLT × After^{1,2}	-0.004***	-0.003***
	(-4.07)	(-2.92)
PLT × After^{3+}	-0.002***	-0.002***
	(-3.22)	(-2.58)
Controls	No	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	22,492	22,492
Adjusted-R^2	0.587	0.632

Panel B: Placebo analysis

	(1) Dividend	(2) Dividend
PLT × Post_Pseudo	-0.001	
	(-0.96)	
PLT_Pseudo × Post		-0.000

		(-0.47)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	22,492	22,492
Adjusted-R^2	0.630	0.631

Figure 1. The impact of green credit policy on dividend policies

This figure shows the dynamic impact of green credit policy on firms' dividend policies. We replace the *Post* indicator with eight dummy variables namely $Before^4$, $Before^3$, $Before^2$, $Before^1$, $After^1$, $After^2$, $After^3$, and $After^4$ to investigate the effects of green credit policy before and after its implementation. We employ the following difference-in-differences model:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Before_t^4 + \beta_2 PLT_{i,t} \times Before_t^3 + \beta_3 PLT_{i,t} \times Before_t^2 + \beta_4 PLT_{i,t} \times Before_t^1 + \beta_5 PLT_{i,t} \times After_t^1 + \beta_6 PLT_{i,t} \times After_t^2 + \beta_7 PLT_{i,t} \times After_t^3 + \beta_8 PLT_{i,t} \times After_t^4 + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

PLT is an indicator variable equal to one if a firm is in a polluting industry, and zero otherwise. $Before^4$ is set to one for the period four years before the green credit policy. $Before^3$ is set to one for the three years before the green credit policy. $Before^2$ is set to one for the two years before the green credit policy. $Before^1$ is set to one for the one year before the green credit policy. $After^1$ is set to one for the one year after the green credit policy. $After^2$ is set to one for the two years after the green credit policy. $After^3$ is set to one for the three years after the green credit policy. $After^4$ is set to one for the period four years after the green credit policy. We include firm and year fixed effects. We report the estimated coefficients as well as their 95% confidence intervals (in the dashed lines represent), adjusted for firm-level clustering.

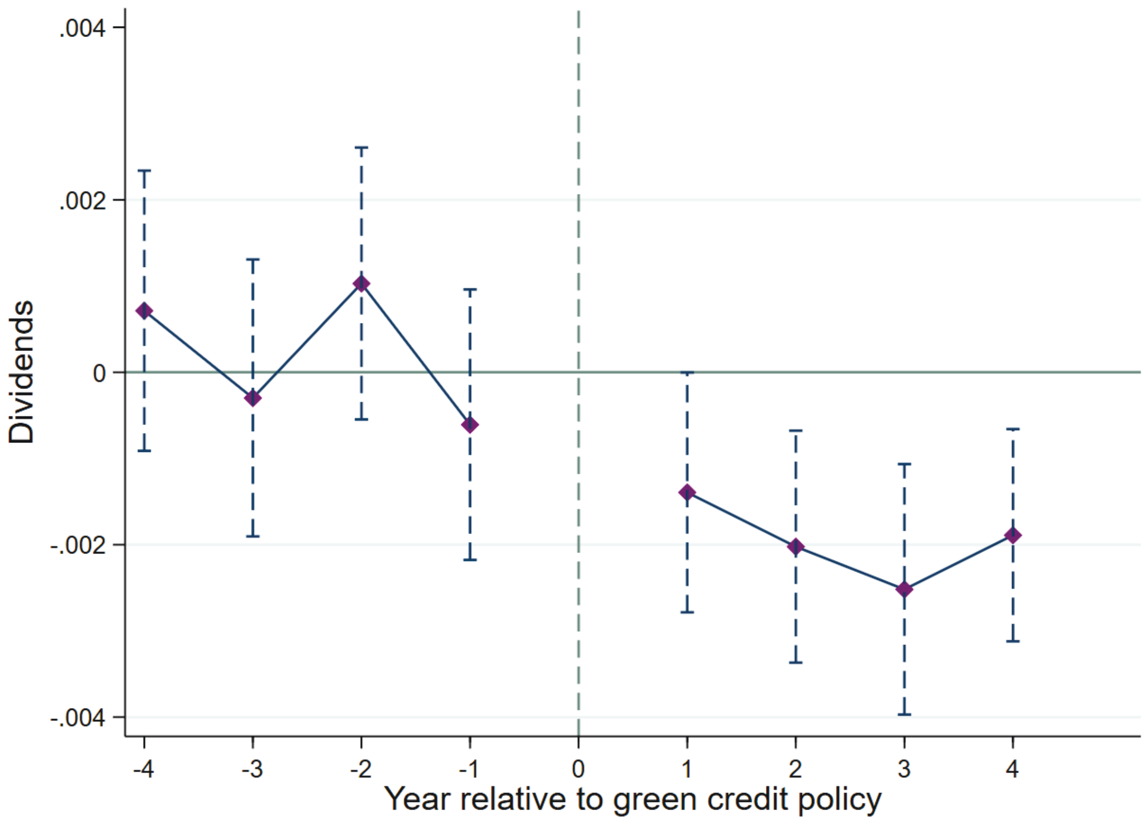

Table 4. PSM-DID analysis

This table reports the difference-in-difference results using the propensity score matched sample. We use the logit model to estimate the propensity scores on all control variables used in the baseline regression model. The matching is carried out for 2011 and is based on the closest propensity score (within a caliper of 0.005) without replacement. Panel A reports diagnostic statistics for the difference in firm characteristics between the treatment and control groups in year 2011. Panel B reports the regression results based on the matched sample. We employ the following model:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

See appendix for variable definitions. All models include year and firm fixed effects. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Diagnostics statistics – differences in means of variables

	Control firms		Treated firms			
Variables	N	Mean	N	Mean	Mean Difference	*t*-Value
SIZE	430	22.186	430	22.136	0.050	0.525
LEV	430	0.46	430	0.469	-0.009	-0.553
ROA	430	0.048	430	0.046	0.001	0.336
CASH	430	0.172	430	0.173	-0.001	-0.115
MTB	430	1.901	430	2.025	-0.124	-1.258
VOL	430	0.026	430	0.026	0.000	-0.332
OWNCON	430	0.185	430	0.185	0.000	0.003

Panel B. DID Regression with the propensity-score-matched samples

	(1)	(2)
	Dividend	Dividend
PLT × Post	-0.002**	-0.003***
	(-2.48)	(-2.69)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	No
Firm FE	No	Yes
Observations	8721	8721
Adjusted-R^2	0.457	0.670

Table 5. Robustness check

This table presents the robustness checks for the relation between green credit policy and corporate dividend payout. We employ the following model:

$$y_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

Panel A reports the OLS regression results of the effect of green credit policy on *Dividend* using various subsamples. In column (1) of Panel A, we restrict our test window to three years before and after the year of green credit policy. In column (2) of Panel A, we exclude observations in the adoption year 2012. In column (3) of Panel A, we remove the firms that change their industrial classification during the sample period (2007-2017). In column (4) of Panel A, we use subsamples free of non-dividend payers. In column (5) of Panel A, we impose a stricter condition that require firms to maintain dividend payment during the sample period (2007-2017). Panel B presents the regression results of green credit policy on alternative measures of dividend payout. Columns (1) and (2) of Panel B report the OLS regression results of the effect of green credit policy on *DIV1*. Columns (3) and (4) of Panel B report the OLS regression results of the effect of green credit policy on *DIV2*. Columns (5) of Panel B reports the OLS regression results of the effect of green credit policy on *DIV3*. Columns (6) of Panel B reports the logit regression results of the effect of green credit policy on *DIV_DUMUM*. See appendix for all variable definitions. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Subsamples

	2009-2015	Excluding the implementation year 2012	Excluding the firms that change industrial code	Excluding the samples that dividend payout is zero	Only including the firms that maintain dividend payout
	(1)	(2)	(3)	(4)	(5)
	Dividend	Dividend	Dividend	Dividend	Dividend
PLT × Post	-0.002**	-0.002***	-0.003***	-0.003**	-0.005**
	(-2.18)	(-2.74)	(-3.02)	(-2.35)	(-2.47)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	14,204	20,394	14,439	14,910	7006
Adjusted-R^2	0.670	0.627	0.664	0.688	0.718

Panel B: Alternative measures of dividend payout

	(1)	(2)	(3)	(4)	(5)	(6)
	DIV1	DIV1	DIV2	DIV2	DIV3	DIV_DUM
PLT × Post	-0.018***	-0.014**	-0.001**	-0.002***	-0.002**	-0.395***
	(-2.79)	(-2.30)	(-2.34)	(-3.29)	(-2.21)	(-4.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	No	Yes
Firm FE	No	Yes	No	Yes	Yes	No
Observations	22,492	22,492	22,492	22,492	22,492	22,492
Adjusted-R^2	0.126	0.334	0.278	0.433	0.618	0.324

Table 6. The role of financial constraints

This table presents the impact of green credit policy on firm level dividend payout with various degrees of financial constraints (columns (1) to (3)). We employ the following model:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \beta_2 PLT_{i,t} \times Post_t \times FC_{i,t} + \beta_3 \times FC_{i,t} + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

Where $FC_{i,t}$ denotes one of three dummy variables used to measure corporate financial constraints, namely *DUMKZ*, *DUMWW,* or *DUMSA*. Specifically, *DUMKZ* is an indicator variable that is equal to one if a firm has an above-median KZ index, and zero otherwise. *DUMWW* is an indicator variable that is equal to one if a firm has an above-median WW index, and zero otherwise. *DUMSA* is an indicator variable that is equal to one if a firm has an above-median SA index, and zero otherwise. To economize on space, all control variables, firm effects, and year effects are suppressed. See appendix for all variable definitions. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Dividend	(2) Dividend	(3) Dividend
PLT × Post	-0.001	-0.001	0.000
	(-1.06)	(-0.65)	(0.11)
PLT × Post × DUMKZ	-0.003**		
	(-2.24)		
PLT × Post × DUMWW		-0.002***	
		(-3.12)	
PLT × Post × DUMSA			-0.003**
			(-2.47)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	22,492	22,492	22,492
Adjusted-R^2	0.634	0.633	0.636

Table 7. The role of corporate governance

This table presents the impact of green credit policy on firm level dividend payout with various degrees of corporate governance. We employ the following model:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \beta_2 PLT_{i,t} \times Post_t \times Gov_{i,t} + \beta_3 \times Gov_{i,t} + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

Where $Gov_{i,t}$ denotes one of four dummy variables used to measure corporate governance, namely *ANALYST*, *VISIT*, *INSOWN*, or *SOE*. Specifically, *ANALYST* is an indicator variable that is equal to one if a firm's followed analysts or analyst teams is below the sample median, and zero otherwise. *VISIT* is an indicator variable that is equal to one if a firm has a below-median number of analyst visits, and zero otherwise. *INSOWN* is an indicator variable that is equal to one if a firm has a below-median ratio of institutional investor shareholdings, and zero otherwise. *SOE* is an indicator variable that is equal to one if a firm is a state-owned enterprise, and zero otherwise. To economize on space, all control variables, firm effects, and year effects are suppressed. See appendix for all variable definitions. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Dividend	(2) Dividend	(3) Dividend	(4) Dividend
PLT × Post	-0.001	-0.001	0.000	-0.000
	(-0.78)	(-0.84)	(0.46)	(-0.80)
PLT × Post × ANALYST	-0.002***			
	(-2.79)			
PLT × Post × VISIT		-0.002**		
		(-2.13)		
PLT × Post × INSOWN			-0.002**	
			(-2.08)	
PLT × Post × SOE				-0.002***
				(-3.57)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	22,492	7935	22,492	22,492
Adjusted-R^2	0.632	0.642	0.635	0.637

Table 8. The role of green innovation

This table presents the impact of green credit policy on firm level dividend payout with various degrees of green innovation. We employ the following model:

$$Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \beta_2 PLT_{i,t} \times Post_t \times Green\_INNO_{i,t} + \beta_3 \times Green\_INNO_{i,t} + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

Where $Green\_INNO_{i,t}$ denotes one of three dummy variables used to measure corporate green innovation, namely *INNO_APP*_DUM, *INNO_GN_DUM,* or *INNO_CITE_DUM*. Specifically, *INNO_APP*_DUM is an indicator variable that is equal to one if a firm is with above-median number of green patent applications in a given year, and zero otherwise. *INNO_GN_DUM* is an indicator variable that is equal to one if a firm is with above-median number of green patents obtained in a given year, and zero otherwise. *INNO_CITE_DUM* is an indicator variable that is equal to one if a firm is with above-median number of green patents cited in a given year, and zero otherwise. To economize on space, all control variables, firm effects, and year effects are suppressed. See appendix for all variable definitions. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Dividend	(2) Dividend	(3) Dividend
PLT × Post	-0.001	-0.001	-0.001
	(-1.05)	(-1.62)	(-1.35)
PLT × Post × INNO_APP_DUM	-0.003**		
	(-2.41)		
PLT × Post × INNO_GN_DUM		-0.002**	
		(-2.30)	
PLT × Post × INNO_CITE_DUM			-0.002**
			(-2.40)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	22,492	22,492	22,492
Adjusted-R^2	0.635	0.635	0.635

Table 9. Green credit policy, liquidity, and financing decisions

This table presents the OLS regression results of the effect of green credit policy on firms' cash holdings, bank loans, and other financing activities. We employ the following model:

$$y_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \delta' \times Controls_{i,t} + \varepsilon_{i,t}$$

We employ a variety of corporate lending indicators, as well as internal and external financing indicators, as dependent variables. *Loan* is the ratio of bank loans to total assets; *Short Loan* is the ratio of short-term bank loans (loan term ≤ one year) to total assets; *Long Loan* is the ratio of long-term bank loans (loan term >one year) to total assets; *Short Loan Ratio* is the ratio of short-term bank loans (loan term ≤ one year) to bank loans; *CASH* is the ratio of cash plus cash equivalents to total assets; *SEO* is the amount of money collected through seasoned equity offerings at the year divided by total assets; *BOND* is the ratio of bond payable to total assets; *Supplier Financing* is the ratio of payables to total assets; See appendix for all variable definitions. *LEV* is total debt divided by total assets; The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Verification of green credit policy: bank credit supply

	(1)	(2)	(3)	(4)
	Loan	Short Loan	Long Loan	Short Loan Ratio
PLT × Post	-0.020***	0.002	-0.018***	0.057***
	(-3.71)	(0.33)	(-4.65)	(4.22)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	17202	17202	17202	17202
Adjusted- R^2	0.798	0.705	0.688	0.611

Panel B: Liquidity and various financing decisions

	(1)	(2)	(3	(4)	(5)
	CASH	SEO	BOND	Supplier Financing	LEV
	0.012**	0.022	-0.003***	0.004**	-0.012**
PLT × Post	(2.45)	(1.11)	(-3.01)	(2.10)	(-2.50)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	22088	2776	22492	22492	22492
Adjusted- R^2	0.569	0.404	0.121	0.564	0.768

Table 10. Green credit policy and corporate dividend smoothing

This table shows results of the following regression:

$$\Delta Dividend_{i,t} = \alpha + \beta_1 Dividend_{i,t-1} + \beta_2 PLT_{i,t} \times Post_t \times Dividend_{i,t-1} + \beta_3 PLT_{i,t} \times Post_t + \beta_4 ROA_{i,t} + \varepsilon_{i,t}$$

Where $Dividend_{i,t-1}$ is the dividend payout divided by the total assets of firm i at the end of year t-1. For the definitions of all the variables and the details of their construction, see appendix. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ∆ Dividend
$Dividend_{t-1}$	-0.652***
	(-27.78)
PLT × Post × $Dividend_{t-1}$	-0.119**
	(-2.35)
PLT × Post	0.002***
	(2.93)
ROA	0.000
	(0.93)
Constant	0.008***
	(25.88)
Year FE	Yes
Firm FE	Yes
Observations	19660
Adjusted-R^2	0.310

Appendix A. Variable definitions

Dividend is the cash dividend payout scaled by total assets.

DIV1 is the cash dividend payout scaled by net earnings.

DIV2 is the cash dividend payout scaled by market value of equity.

DIV_DUM is a dummy variable that equals one if a firm pays cash dividend payout, and zero otherwise.

DIV3 is calculated as corporate cash dividend payout subtracted by the mean dividend payout of all firms within the same province, normalized by total assets.

PLT is an indicator variable that equals one if a firm is in a polluting industry, and zero otherwise.

Post is an indicator variable that equals one for 2012 and later, and zero otherwise.

SIZE is the natural logarithm of total assets.

LEV is total debt divided by total assets.

ROA is net profit divided by total assets.

CASH is the ratio of cash plus cash equivalents to total assets.

MTB is book value of total assets minus book value of equity plus market value of equity divided by book value of total assets.

VOL is the standard deviation of daily stock returns over the year.

OWNCON is the sum of the squares of the percentage of shareholdings held by the ten largest shareholders.

Before^{3+} is an indicator variable that is equal to one for observations with three years or more prior to the green credit policy, and zero otherwise.

Before^{1,2} is an indicator variable that is equal to one for observations with one or two years prior to the green credit policy, and zero otherwise.

After^{0} is an indicator variable that is equal to one for the year of green credit policy, and zero otherwise.

After^{1,2} is an indicator variable that is equal to one for observations with one- or two-years post-policy, and zero otherwise.

After^{3+} is an indicator variable that is equal to one for observations with three years or more post-policy, and zero otherwise.

Before^{4} is set to one for the period four years before the green credit policy, and zero otherwise.

Before^{3} is set to one for the three years before the green credit policy, and zero otherwise.

Before^{2} is set to one for the two years before the green credit policy, and zero otherwise.

Before^{1} is set to one for the one year before the green credit policy, and zero otherwise.

After^{1} is set to one for the one year after the green credit policy, and zero otherwise.

After^{2} is set to one for the two years after the green credit policy, and zero otherwise.

After^{3} is set to one for the three years after the green credit policy, and zero otherwise.

After^{4} is set to one for the period four years after the green credit policy, and zero otherwise.

Post_Pseudo is an indicator variable that is equal to one for year after the pseudo-event-year (2010), and zero otherwise.

PLT_Pseudo is an indicator variable that is equal to one if a firm is in a randomly assigned polluting industry, and zero otherwise.

ANALYST is an indicator variable that is equal to one if a firm's followed analysts or analyst teams is below the sample median, and zero otherwise.

VISIT is an indicator variable that is equal to one if a firm has a below-median number of analyst visits, and zero otherwise.

INSOWN is an indicator variable that is equal to one if a firm has a below-median ratio of institutional investor shareholdings, and zero otherwise.

SOE is an indicator variable that is equal to one if a firm is a state-owned enterprise, and zero otherwise.

*INNO_APP*_DUM is an indicator variable that is equal to one if a firm is with above-median number of green patent applications in a given year, and zero otherwise.

INNO_GN_DUM is an indicator variable that is equal to one if a firm is with above-median number of green patents obtained in a given year, and zero otherwise.

INNO_CITE_DUM is an indicator variable that is equal to one if a firm is with above-median number of green patents cited in a given year, and zero otherwise.

DUMKZ is an indicator variable that is equal to one if a firm has an above-median KZ-index, and zero otherwise. Following (Kaplan & Zingales, 1997), $KZ\text{-}index = -1.002 \times CF - 39.368 \times Div + 3.139 \times Lev + 0.283 \times Q - 1.315 \times Cash$, where *CF* is net cash flows from operating activities divided by total assets at the beginning of the year; *Div* is dividend payout divided by total assets at the beginning of the year; *Lev* is total debt divided by total assets; *Q* is book value of total assets minus book value of equity plus market value of equity divided by book value of total assets; *Cash* is cash plus cash equivalents divided by total assets at the beginning of the year.

DUMWW is an indicator variable that is equal to one if a firm has an above-median WW-index, and zero otherwise. Following (Whited & Wu, 2006), $WW\text{-}index = -0.091 \times CF - 0.062 \times DivPos + 0.021 \times Lev - 0.044 \times Size + 0.102 \times ISG - 0.035 \times SG$, where *CF* is net cash flows from operating activities divided by total assets; *DivPos* is an indicator variable that is equal to one if a firm pays dividend payout, and zero otherwise; *Lev* is total debt divided by total assets; *Size* is the natural logarithm of total assets; *ISG* is average industry sales growth; *SG* is firm sales growth.

DUMSA is an indicator variable that is equal to one if a firm has an above-median SA-index, and zero otherwise. Following (Hadlock & Pierce, 2010), $SA\text{-}index = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age$, where *Size* is the natural logarithm of total assets; *Age* is the number of years the firm has been listed on the Shanghai Stock Exchange or Shenzhen Stock Exchange.

Loan is the ratio of bank loans to total assets.

Short Loan is the ratio of short-term bank loans (loan term ≤ one year) to total assets.

Long Loan is the ratio of long-term bank loans (loan term >one year) to total assets.

Short Loan Ratio is the ratio of short-term bank loans (loan term ≤ one year) to bank loans.

SEO is the amount of money collected through seasoned equity offerings at the year divided by total assets.

BOND is the ratio of bond payable to total assets.

Supplier Financing is the ratio of payables to total assets;

Online appendix OA1. Additional Robustness Check

In the main regression, we use level data for both the dependent variable and independent variables. However, there may be endogeneity concerns associated with this approach. To address this concern and strengthen the robustness of our main findings, we adopt the methodology of Bliss, Cheng, and Denis (2015) in building our model. Our model uses the change in dividend rate as the dependent variable and includes lags for the regressors. Specifically, we employ the following model:

$$\begin{aligned}\Delta Dividend_{i,t} = {} & \alpha + \beta_1 PLT_{i,t} \times Post_t + \beta_2 SIZE_{i,t-1} + \beta_3 LEV_{i,t-1} + \beta_4 ROA_{i,t-1} \\ & + \beta_5 CASH_{i,t-1} + \beta_6 MTB_{i,t-1} + \beta_7 VOL_{i,t-1} + \beta_8 OWNCON_{i,t-1} \\ & + Year_t + Industry_j + Firm_i + \varepsilon_{i,t}\end{aligned}$$

Where *ΔDividend* is calculated as the ratio of change in the amount of a firm's dividend payout; *PLT* is set to one if a firm is in a polluting industry, and zero otherwise; *Post* is set to one for 2012 and later, and zero otherwise. For the definitions of all the variables and the details of their construction, see appendix. The standard errors in the regressions are clustered at the firm level.

Table OA1 presents the regression results. In column (1), we exclude firm-level control variables while controlling for year- and industry-fixed effects. Similarly, in column (2), we also do not incorporate firm-level control variables, but instead, control for year- and firm-fixed effects. In column (3), we include firm-level control variables while controlling for year- and industry-fixed effects. Finally, in column (4), we include firm-level control variables and control for year- and firm-fixed effects. The results show that the coefficient on the interaction term between *PLT* and *Post* is significantly negative across all columns, i.e., from (1) to (4), indicating that polluting firms experienced a significantly larger decline in cash dividends compared to non-polluting firms after the implementation of the green credit policy. These results further support our main findings.

Online appendix OA2. Green credit policy and bank loans (Industry-level)

In this section, we use industry-level data to reassess the impact of the green credit policy on bank loans of firms. Specifically, we employ the following model:

$$\bar{y}_{j,t} = \alpha + \beta_1 \overline{PLT}_{j,t} \times \overline{Post}_t + \beta_2 \overline{AGE}_{j,t-1} + \beta_3 \overline{ROA}_{j,t-1} + \beta_4 \overline{LEV}_{j,t-1} + \beta_5 \overline{GROWTH}_{j,t-1} + \beta_6 \overline{B\_SIZE}_{j,t-1} + \beta_7 \overline{B\_IND}_{j,t-1} + \beta_8 \overline{TOP1}_{j,t-1} + Year_t + Industry_j + \varepsilon_{j,t}$$

Where $\bar{y}_{j,t}$ refers to the industry loan growth rate ($\Delta\overline{Loan}$), industry short-term loan growth rate ($\Delta\overline{Short\ Loan}$), or industry long-term loan growth rate ($\Delta\overline{Long\ Loan}$). Specifically, $\Delta\overline{Loan}$ is measured as the average of the loan growth rate of all companies in the industry. Similarly, $\Delta\overline{Short\ Loan}$ is measured as the average of short-term loan (loan term $\leqslant$ one year) growth rate of all companies in the industry. Finally, $\Delta\overline{Long\ Loan}$ is measured as the average of long-term loan (loan term > one year) growth rate of all companies in the industry. All the control variables are industry mean. For the definitions of all the variables and the details of their construction, see appendix. The standard errors in the regressions are clustered at the industry level.

Table OA2 presents the regression results. The coefficients on *PLT* × *Post* in the $\Delta\overline{Loan}$ and $\Delta\overline{Long\ Loan}$ regressions are negative and significant, whereas the coefficient on *PLT* × *Post* in the $\Delta\overline{Short\ Loan}$ regression is insignificant. These results show that polluting industries witnessed a significantly larger decline in the bank loans, especially long-term bank loans, relative to non-polluting industries following the implementation of the green credit policy. Our results are similar to the findings presented in Section 5.1, providing further support for the efficacy of the green credit policy.

Online appendix OA3. Green credit policy and bank loans

In Section 5.1, we investigate the impact of the green credit policy on bank loans of firms. And the results show that banks reduce their loans, especially long-term loans, to these firms following the implementation of the policy. To further strengthen the validity of these results, we employ the firm's loan growth rate as an additional measure of its borrowing capacity in this section, in addition to the loan-to-asset ratio used in Section 5.1. Specifically, we employ the following model:

$$y_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \beta_2 AGE_{i,t-1} + \beta_3 ROA_{i,t-1} + \beta_4 LEV_{i,t-1} + \beta_5 GROWTH_{i,t-1} + \beta_6 B\_SIZE_{i,t-1} + \beta_7 B\_IND_{i,t-1} + \beta_8 TOP1_{i,t-1} + Year_t + Firm_i + \varepsilon_{i,t}$$

Where $y_{i,t}$ refers to the loan growth rate (*ΔLoan*), short-term loan growth rate (*ΔShort Loan*), or long-term loan growth rate (*ΔLong Loan*). Specifically, *ΔLoan* is the difference between a firm's bank loans in year t and year t-1, normalized by the firm's bank loans in year t-1. Similarly, *ΔShort Loan* is the difference between a firm's short-term bank loans (loan term ≤ one year) in year t and year t-1, normalized by the firm's short-term bank loans in year t-1. Finally, *ΔLong Loan* is the difference between a firm's long-term bank loans (loan term > one year) in year t and year t-1, normalized by the firm's long-term bank loans in year t-1. For the definitions of all the variables and the details of their construction, see appendix. The standard errors in the regressions are clustered at the firm level.

Table OA3 presents the regression results. The coefficients on *PLT* × *Post* in the *ΔLoan* and *ΔLong Loan* regressions are negative and significant at the 5% level, and the coefficient on *PLT* × *Post* in the *ΔShort Loan* regression is significant at the 10% level. These results show that polluting firms witnessed a significantly larger decline in the bank loans, especially long-term bank loans, relative to non-polluting firms following the implementation of the green credit policy. Our results are consistent with the findings presented in Section 5.1 and OA2, providing further support for the efficacy of the green credit policy.

References

Bliss, B. A., Cheng, Y., & Denis, D. J. (2015). Corporate payout, cash retention, and the supply of credit: Evidence from the 2008–2009 credit crisis. *Journal of Financial Economics*, *115(3)*, 521-540.

Table OA1. Alternative robust tests: green credit policy and corporate dividend policies

This table presents the OLS regression results of the effect of green credit policy on firms' dividend policies. We employ the following difference-in-differences model:

$$\Delta Dividend_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \beta_2 SIZE_{i,t-1} + \beta_3 LEV_{i,t-1} + \beta_4 ROA_{i,t-1} + \beta_5 CASH_{i,t-1} + \beta_6 MTB_{i,t-1} + \beta_7 VOL_{i,t-1} + \beta_8 OWNCON_{i,t-1} + Year_t + Industry_j + Firm_i + \varepsilon_{i,t}$$

The sample consists of 19,064 firm–year observations from 2007 to 2017. Δ *Dividend* is calculated as the ratio of change in the amount of a firm's dividend payout. *PLT* is set to one if a firm is in a polluting industry, and zero otherwise. *Post* is set to one for 2012 and later, and zero otherwise. For the definitions of all the variables and the details of their construction, see appendix. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Δ Dividend	(2) Δ Dividend	(3) Δ Dividend	(4) Δ Dividend
PLT × Post	-0.026***	-0.027*	-0.029***	-0.037**
	(-2.68)	(-1.78)	(-2.95)	(-2.28)
Controls	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	19064	19064	19064	19064
Adjusted-R^2	0.000	-0.051	0.001	-0.045

Table OA2. Regression analysis on bank loans using industry average data

This table presents the OLS regression results of the effect of green credit policy on firms' bank loans, using data at the industry level. We employ the following difference-in-differences model:

$$\bar{y}_{j,t} = \alpha + \beta_1 \overline{PLT}_{j,t} \times \overline{Post}_t + \beta_2 \overline{AGE}_{j,t-1} + \beta_3 \overline{ROA}_{j,t-1} + \beta_4 \overline{LEV}_{j,t-1} + \beta_5 \overline{GROWTH}_{j,t-1} + \beta_6 \overline{B\_SIZE}_{j,t-1} + \beta_7 \overline{B\_IND}_{j,t-1} + \beta_8 \overline{TOP1}_{j,t-1} + Year_t + Industry_j + \varepsilon_{j,t}$$

The sample consists of 680 industry–year observations from 2007 to 2017. The dependent variables are $\Delta\overline{Loan}$, $\Delta\overline{Short\ Loan}$, or $\Delta\overline{Long\ Loan}$. $\Delta\overline{Loan}$ is measured as the average of the loan growth rate of all companies in the industry. $\Delta\overline{Short\ Loan}$ is measured as the average of short-term loan (loan term ⩽ one year) growth rate of all companies in the industry. $\Delta\overline{Long\ Loan}$ is measured as the average of long-term loan (loan term > one year) growth rate of all companies in the industry. *PLT* is set to one if a firm is in a polluting industry, and zero otherwise. *Post* is set to one for 2012 and later, and zero otherwise. All the control variables are industry mean. For the definitions of all the variables and the details of their construction, see appendix. The standard errors in the regressions are clustered at the industry level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) $\Delta\overline{Loan}$	(2) $\Delta\overline{Short\ Loan}$	(3) $\Delta\overline{Long\ Loan}$
PLT × Post	-0.069**	-0.052	-0.082**
	(-2.00)	(-1.15)	(-2.15)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	680	680	680
Adjusted-R^2	0.066	0.037	0.026

Table OA3. Alternative robust tests: green credit policy and bank loans

This table presents the OLS regression results of the effect of green credit policy on bank loans of firms. We employ the following difference-in-differences model:

$$y_{i,t} = \alpha + \beta_1 PLT_{i,t} \times Post_t + \beta_2 AGE_{i,t-1} + \beta_3 ROA_{i,t-1} + \beta_4 LEV_{i,t-1} + \beta_5 GROWTH_{i,t-1} + \beta_6 B\_SIZE_{i,t-1} + \beta_7 B\_IND_{i,t-1} + \beta_8 TOP1_{i,t-1} + Year_t + Firm_i + \varepsilon_{i,t}$$

The sample consists of 14,327 firm–year observations from 2007 to 2017. The dependent variables are △*Loan*, △*Short Loan*, or △*Long Loan*. △*Loan* is the difference between a firm's bank loans in year t and year t-1, normalized by the firm's bank loans in year t-1; △*Short Loan* is the difference between a firm's short-term bank loans (loan term ≤ one year) in year t and year t-1, normalized by the firm's short-term bank loans in year t-1; △*Long Loan* is the difference between a firm's long-term bank loans (loan term > one year) in year t and year t-1, normalized by the firm's long-term bank loans in year t-1; *PLT* is set to one if a firm is in a polluting industry, and zero otherwise. *Post* is set to one for 2012 and later, and zero otherwise. For the definitions of all the variables and the details of their construction, see appendix. The standard errors in the regressions are clustered at the firm level. The numbers reported in parentheses are *t*-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	△ Loan	△ Short Loan	△ Long Loan
PLT × Post	-0.060**	-0.058*	-0.076**
	(-2.21)	(-1.80)	(-2.11)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	14327	14327	14327
Adjusted-R^2	0.106	0.044	-0.020