Banking on Forest

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Abstract

This paper examines whether a firm's exposure to deforestation risk affects loan terms. We find that forest-dependent firms face higher loan spreads than their peers when forest loss is driven by wildfires. In contrast, when forest loss is human-induced, the gap in spreads becomes significant only after the European Commission proposed the deforestation regulatory framework. Firms obtaining loans in the aftermath of human-induced deforestation subsequently reduce their reliance on forest-based inputs from suppliers in high-risk countries, initiate reforestation efforts, and divest from pollutive deforested plants. Our findings highlight banks' compliance role in green transition.

Keywords: deforestation, bank lending, environmental policy, green transition
JEL Classification: G21, G28, G30, Q54

1 Introduction

Forest loss can be the reason for economic loss in the form of natural disasters, or the consequence of economic activities such as agricultural land use and urbanization. The first, mostly driven by wildfires, accounts for nearly a quarter of global forest loss[1], represents an *acute physical risk* that immediately reduces the ecosystem services essential to a firm's production[2]. In contrast, human-induced forest loss, mainly driven by the conversion of forests into agricultural land, contributes to *chronic physical risks* by driving long-term climate change, including increased carbon emissions and desertification (e.g., Van der Werf et al. 2009, Pan et al. 2011, Houghton et al. 2012).

Various international organizations have introduced initiatives and frameworks to encourage the green transition toward less forest-degrading production and supply chains.[3] [4] Among which, the European Union Deforestation Regulation (EUDR) [5] mandates due diligence for commodities linked to deforestation.[6] This creates significant *transitions risk* for firms whose production processes are tied to deforestation and rising costs from litigation for non-compliance and market disruptions driven by shifting supply and demand.

Given firms' exposure to forest-loss related climate risks (FSB 2017), banks, as primary creditors, must not only ensure regulatory compliance (see, e.g., Allen et al. 2024, De Haas

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[1] Studies show the sub-regional patterns of wildfire increase in terms of length and intensity over the past several decades. Such increase is directly associated with changes in weather and climate other than previous land uses (e.g., Westerling et al. 2006, Jolly et al. 2015).
[2] For instance, the California wildfires in 2018 caused an estimated \$148.5 billion damages (1.5% of state's GDP), including \$27.7 billion capital losses, \$32.2 billion health costs and \$88.6 billion indirect losses (Wang et al. 2021).
[3] Popp et al. (2014) estimate that, without land-use regulations, human-induced forest loss could contribute 13% of the global carbon budget needed to meet the Paris Agreement's 2°C target by 2050. With conservation measures like REDD+, this could be reduced to 7%.
[4] For example, REDD+ (Reducing Emissions from Deforestation and Forest Degradation) was established under the UNFCCC's Warsaw Framework in 2013 as a climate mitigation strategy. The OECD-FAO Guidance, introduced in 2016, helps businesses manage risks in agricultural supply chains.
[5] EUDR timeline: deforestation regulation framework proposal (July 23, 2019), legislative proposal (November 17, 2021), official agreement (December 6, 2022), entry into force (June 29, 2023). The compliance deadline for medium and large companies is December 30, 2025, and for small and micro enterprises is June 30, 2026.
[6] Under EUDR Article 2(15), an operator is any entity placing or exporting regulated products. This includes firms transforming one Annex I (regulated) product into another, such as cocoa butter into chocolate. https://green-business.ec.europa.eu/deforestation-regulation-implementation_en.

2023) and address scrutiny from their own shareholders (see, e.g., Krueger et al. 2020, Giglio et al. 2021), but also actively manage and adjust their lending portfolios. This paper sets to examine how banks use the syndicated loan contracts to cope with borrower's physical and transition risks associated with forest loss.

We compile a global sample from 2002 to 2024 from various datasets. The information on syndicated loan comes from DealScan. We use forest loss geospatial data from Global Land Analysis and Discovery (GLAD) laboratory at University of Maryland (Hansen et al. 2013; Tyukavina et al. 2022) and geocode firms' headquarters within a 10-kilometer radius to differentiate fire-induced and human-induced forest loss. We assess firms' reliance on forest-related ecosystem services with the tool of Exploring Natural Capital Opportunities, Risks and Exposure (ENCORE), which evaluates economic activities based on their dependency on ecosystem services and their impact on natural capital. Our final loan-level sample consists of 42,590 transactions, covering 6,329 borrowers and 1,298 lenders, with significant representation from the U.S., EU, and other OECD countries.

First of all, we find that banks charge higher loan spreads for forest-dependent firms affected by fire-induced forest loss, with firms facing a 12-65 basis point (bps) higher yield spread relative to other borrowers. Second, we examine the impact of the EUDR and observe that the effect of fire-induced forest loss on loan pricing remains stable before and after the EUDR proposal; in contrast, the effect of human-induced loss becomes significant only in the post-EUDR period: on average, one-standard-deviation change in human-induced loss is associated with an 8.1bps increase in yield spreads for forest dependent firms. Year-by-year regressions further suggest that yield spreads for firms experiencing human-induced loss began rising following the 2016 Paris Agreement and became significantly positive from 2020 onward, aligning with the timeline of the EUDR proposal.

Across banks and borrowers, EU banks charge significantly higher spreads to EU forest-dependent firms exposed to human-induced loss, compared to the others. The effect is significant for OECD banks lending to OECD borrowers, but the magnitude is smaller, suggesting that while the EUDR has a strong regulatory influence within the EU, its effects extend—though less intensely—to other OECD countries. Over the course of the EUDR's implementation, one-standard-deviation change in human-induced loss is associated with a 43.5 bps increase in yield spreads for EU banks lending to EU firms between the regulation's proposal in July 2019 and its entry into force in June 2023. The effect rises to 46.9 bps from July 2023 onward. In contrast, the effect is not significant for non-EU banks lending to non-EU firms. When incorporating country-level forest loss risk, the pricing effect for EU firms nearly doubles, highlighting how banks increasingly incorporate transition risks into lending decisions as compliance deadlines approach.

To examine whether banks price actual physical disruptions to firms' operations or merely perceived risk, we compare changes in firms' cash flows following substantial forest loss of both types. We find that large fire-induced loss is associated with a decline in firm's operating cash flows, suggesting tangible operational impacts, while large human-induced loss has no significant effect on short-term cash flows, suggesting limited immediate impact on operations. These findings suggest that banks raise lending interest rates in response to fire-induced loss because if it reflects real impact on short-term liquidity, whereas the absence of a similar response to human-induced loss is consistent with its lack of short-term operational consequences.

Next, we examine how borrowers adapt to rising financing costs and transition risks associated with deforestation. First, firms that actively disclose anti-deforestation commitments experience reduced loan pricing penalties. While such commitments had no significant effect prior to the EUDR, in the post-EUDR period, the interaction between firm commitment and human-induced forest loss becomes significantly negative, suggesting that proactive firms can mitigate spread increases. Second, following substantial human-induced forest loss, firms do not reduce their overall reliance on forest-based inputs but shift sourcing toward countries with lower deforestation risk. Additionally, firms securing loans after human-induced loss demonstrate increased reforestation activity, as measured by the Normalized Difference Vegetation Index (NDVI), a proxy for vegetation greenness—an effect that is particularly strong among highly forest-dependent firms. In contrast, we find limited evidence that firms adjust their supply chains or engage in reforestation following fire-induced forest loss. Finally, we find that firms also respond to transition risks by adjusting their asset portfolios, notably through the divestment of pollutive, forest-dependent plants.

By examining how banks price syndicated loans for borrowers exposed to deforestation risk, this paper makes several key contributions to the literature. First, it uncovers a new stylized practice of syndicated lenders in assessing and pricing climate physical risks, shedding light on how financial institutions integrate environmental factors into loan pricing. A few prior studies suggest that banks price climate physical risks such as natural disasters. For instance, Brown et al. (2021) show that after severe winter weather, banks respond to firms' increased demand for capital by raising loan costs. Besides, Correa et al. (2022) find that loan spreads rise even for firms not directly impacted by natural disasters but with a high likelihood of exposure, suggesting that higher borrowing costs stem from lenders adjusting their expectations of climate risks. We show that forest-dependent firms affected by fire-induced forest loss face a 12-65 bps higher yield spread, economically more significant than differences due to relationship lending (10-17 bps gap between relationship and non-relationship lending in Bharath et al., 2011). In addition, our work is related to the literature of how banks mitigate physical risks in lending, including banks' divestment (e.g., Blickle et al. 2021, Ilabaca et al. 2024) and price adjustment (e.g., Javadi and Masum 2021, Nguyen et al. 2022, Götz et al. 2024) in syndicated loans and mortgages, to manage the credit risks from firms affected by natural disasters.

Second, this paper highlights the pivotal role of regulation in shaping capital market practices and leveraging financial institutions as key agents for policy implementation. This underscores how regulatory frameworks and environmental policies, such as the EUDR, influence risk assessment and capital allocation. This observation echoes the prior findings that climate initiatives and regulations spur lenders to re-allocate capital and tighten the loan terms. For example, Kacperczyk and Peydró (2022) show that banks re-allocate credit from brown to green firms after committing to carbon neutrality Science Based Targets initiative (SBTi); Degryse et al. (2023) document that banks offer cheaper loans to green firms following the Paris Agreement; Ivanov et al. (2024) find that cap-and-trade bills tighten bank loan terms for high-emission firms.

Third, we provide direct firm-level evidence that climate regulations like the EUDR can drive operational changes, prompting firms to adopt more environmentally sustainable practices. This demonstrates the tangible impact of financial and regulatory pressures in steering corporate behavior toward greener outcomes. This finding aligns with the existing literature showing that regulatory pressures push firms toward greener production and investment strategies. For instance, Goetz (2019) finds that firms reduce toxic emissions when lower capital costs enable greater investment in pollution prevention. Accetturo et al. (2022) show that increased credit supply raises the likelihood of firms' green investments in cleaner production technologies. Apicella and Fabiani (2023) document that firms exposed to carbon pricing expand credit demand and reduce emissions, highlighting how financing facilitates greener operations.

Finally, this paper introduces the concept of deforestation risk and the two types of forest loss to the finance literature. By linking these environmental disruptions to widely recognized climate risks, we show that financial institutions and firms acknowledge their threats and respond through risk management strategies and operational adjustments. This contributes to the literature on environmental action versus greenwashing (e.g., Kacperczyk and Peydró 2022, Giannetti et al. 2024, Sastry et al. 2024). In addition, we find forest-dependent firms' disclosures on addressing deforestation issues mitigate the loan pricing difference, aligning with Carbone et al. (2022), who show that firms' stating emission and reduction targets in disclosures is linked to lower credit risk, particularly for firms with more ambitious commitments.

The remainder of the paper is structured as follows: Section 2 describes the data and sample. Section 3 outlines the empirical model and specifications, while Section 4 presents and discusses the empirical results. Section 5 concludes.

2 Data and sample construction

We compile a loan-level sample (2002-2024) from multiple sources for our main analyses. Geospatial data on global forest loss are obtained from the Global Land Analysis and Discovery (GLAD) laboratory at the University of Maryland (Hansen et al., 2013; Tyukavina et al., 2022). To capture changes in vegetation greenness, we use the NASA MODIS Normalized Difference Vegetation Index (NDVI). Information on ecosystem dependencies of production processes is sourced from the ENCORE (Exploring Natural Capital Opportunities, Risks and Exposure) tool, maintained and regularly updated by the United Nations. Customer–supplier relationships for U.S. firms are retrieved from Compustat Segment. Climate risk indices are obtained from Li et al. (2024). Corporate disclosures related to deforestation are collected via Refinitiv Advanced Filings Search (AdvFil). Data on plant divestitures are drawn from the EPA's Toxics Release Inventory (TRI) Program and the SDC M&A database. Syndicated loan information is sourced from DealScan, while firm and bank financials are compiled from Compustat Global, Compustat North America, and Refinitiv. We exclude financial firms, regulated utilities, and public administration firms.

We match the new LoanConnector DealScan data with the legacy DealScan dataset using the WRDS mapping utility. To obtain ISIN codes, the old DealScan data are linked to Worldscope via the DealScan–Worldscope Link Table (Beyhaghi et al., 2021). For borrower financial data, we use the link table provided by Schwert (2018) to merge DealScan with Compustat. Lender information is matched using the link table developed by Chava and Roberts (2008). To link Compustat company records with customer identifiers from Compustat Segment, we rely on the mapping tables contributed by Cohen and Frazzini (2008) and Cen (2017).

The combined dataset, used for testing our main hypotheses, is structured at the loan level[7], and contains 42,590 observations across 6,329 unique borrowers. Of these, 2,866 firms (45%) are headquartered in the US, 829 (13%) in the EU, and 4,766 (75%) in OECD member countries. This sample also includes 1,298 unique lenders, with 328 (25%) in the US, 226 (17%) in the EU, and 782 (60%) in OECD countries.

2.1 Measuring forest loss surrounding firm using geospatial data

We rely on two geospatial datasets to measure firm-level forest loss. The first source is the *Global Forest Change 2000-2023* dataset developed by the Global Land Analysis and Discovery (GLAD) laboratory at the University of Maryland (Hansen et al. 2013). The dataset provides high-resolution (30-meter) annual data on gross forest cover loss from 2000 to 2023, derived from Landsat time-series imagery. The forest loss is defined as a stand-replacement disturbance, i.e., a change from a forest to non-forest state. The second source is the *Global forest loss due to fire* dataset developed by Tyukavina et al. (2022). The dataset disaggregates

[7] We follow Chakraborty et al. (2018) to rank and select the lead arrangers with significant share in a deal. The final data for analysis is at the lead arranger-deal-earliest tranche (origination date) level.

the *Global Forest Change* data (Hansen et al. 2013) into forest loss due to fire versus other disturbance drivers, with the same resolution and frequency. Using supervised classification models, the dataset identifies spectral and spatial signatures specific to fires, including only stand-replacement fires (causing full canopy loss) and excluding mechanical burning of felled trees for farming purposes. For our analysis settings, we use the "forest loss due to fire" data to measure the firm-level fire-induced forest loss, and "forest loss due to other disturbance drivers" to measure the firm-level human-induced forest loss. The second measure mainly captures the forest loss induced by the commodity and agricultural activities, as suggested by the classification of global forest loss drivers in Curtis et al. (2018).[8]

Next, we measure the forest loss, both fire and the human-induced, surrounding the headquarters of firms in our sample. We obtain firm address data, including company name, street address, city, county, and country, from Compustat and Refinitiv. To determine precise geographic coordinates, we employ a multi-step, return-selecting search algorithm that interactively queries Google Maps. This approach minimizes geolocation errors that may arise from inaccurate or incomplete address information. Using the resulting coordinates, we measure forest loss within a 10-kilometer radius of each firm's headquarters via Google Earth Engine. Forest loss is categorized into fire-induced and human-induced loss, with the results quantified in square kilometers.

Before integrating the forest loss data with the loan-level sample, we first match it to the DealScan firm-year panel to analyze the distribution of forest loss and construct lagged measures. Figure 1 illustrates the geographic distribution of our sample firms and the surrounding forest loss in 2023. Each firm's headquarter is represented by a visually enlarged circles for clarity, with darker shading indicating greater forest loss within 10km radius. Table

[8] Curtis et al. (2018) identify five main drivers of global forest loss, with three linked to commodity and agricultural activities, accounting for approximately 77% of the total. Wildfires contribute about 23%, while urbanization accounts only for less than 1%.

1 reports the ranking of forest loss across countries. Within our sample, firms in Greece, Portugal and Russia experience the highest average fire-induced loss, with US firms ranking seventh. In terms of human-induced loss, firms in Malaysia have the highest loss, with 1.72 times higher than the firms in Portugal, which ranks second. This aligns with reports identifying Malaysia as having the highest rate of deforestation globally, largely due to commercial agriculture and business-driven land use change.[9] From an industry perspective, Table 2 summarizes the distribution of both types of forest loss across the high-level SIC divisions, excluding financial firms, regulated utilities, and public administration. The summary suggests that all industries are exposed to both types of forest loss, though fire-induced loss varies more widely across industries. Firms in the wholesale trade division exhibit the highest average fire-induced loss, whereas mining firms are most affected by human-induced loss.

[Figure 1] [Table 1 and Table 2]

Table 3 presents summary statistics for fire-induced and human-induced forest loss lagged by one year in both the firm-year panel and the DealScan loan-level sample. In the firm-year sample, firms experience an average of 0.0153 km^2 fire-induced loss and 0.1884 km^2 human-induced loss. These averages are lower in the loan-level sample based on DealScan, which excludes extreme cases of unusually large fire-induced loss.

[Table 3]

2.2 Measuring firms' production forest-dependency

ENCORE (Exploring Natural Capital Opportunities, Risks and Exposure) is a tool launched in 2018 through a collaboration between Global Canopy, the UNEP Finance Initiative, and the UNEP World Conservation Monitoring Centre (UNEP-WCMC). It helps financial

[9] For instance: (1) Malaysia has the world's highest deforestation rate, as revealed by Google's forest map. https://news.mongabay.com/2013/11/malaysia-has-the-worlds-highest-deforestation-rate-reveals-google-forest-map/; (2) Causes of rainforest deforestation in Malaysia. https://www.internetgeography.net/topics/causes-of-rainforest-deforestation-in-malaysia/.

institutions and companies assess the extent to which economic activities depend on nature, and it plays a critical role in evaluating ecosystem-related risks, including biodiversity loss. ENCORE's framework operates through two assessment pathways: (1) the dependency pathway, which evaluates the direct reliance of economic activities on ecosystem services, and (2) the impact pathway, which measures the pressure that economic activities exert on ecosystems. Our study primarily relies on the dependency pathway to identify forest dependencies, as the risks from forest loss are directly linked to the degree to which a firm's operations depend on forest-based ecosystem services. We also draw on the impact pathway to explore whether forest-dependent firms contribute to ecosystem degradation, thereby offering insight into potential regulatory attention these firms may attract. In our sample, approximately 80% of firms with above-median forest dependency also exhibit significantly above-median impacts on forests, underscoring the dual role many firms play as both reliant on and contributors to forest ecosystem risk.

ENCORE carries out a rigorous methodology to assess the dependencies of economic activities on ecosystem services. It conducts extensive literature reviews using standardized search terms across scientific journals, peer-reviewed studies, industry reports, and grey literature. These findings are validated by industry experts, resulting in a comprehensive assessment of the 25 ecosystem services relied upon by 271 economic activities. Each dependency is rated on a six-level materiality scale, ranging from very low to very high.[10] For each industry's production process, ENCORE provides three key data points: (1) a materiality rating on the production process dependency on various ecosystem services[11], (2) the natural

[10] Where no links are identified, the activity-service pair is marked as N/A (Not Applicable) or ND (No Data).
[11] For instance, the production process of "large-scale rainfed arable crops" relies on 18 ecosystem services with varying degrees of dependency. To give an example, ENCORE states this production process is highly dependent on *animal-based energy* service due to its low resilience to disruptions in this ecosystem service. In comparison, the process also has minimal dependence on *water quality*, as the production process can typically continue even in the event of significant disruption to this service.

capital assets required for each ecosystem service and the associated benefits, and (3) the natural or human-induced pressures (e.g., forest loss drivers) affecting these assets' ability to provide goods and services.

In our analysis, we begin by identifying ecosystem services provided by forest-related natural capital assets (referred to as "*forest services*" afterwards for simplicity). For instance, the ecosystem service "climate regulation" depends on the proper functioning of habitats, soils, water, and wetlands. These natural capital assets are classified as forest-related because forest clearance drivers, including "habitat modification" and "overharvesting," can degrade them to an extent. In this case, "climate regulation" will be identified as *forest services*. After selecting only *forest services*, we then aggregate the six-level materiality ratings (we re-assign values from 0-5) of the production process dependency on the *forest services* into the production process level. This approach specifically focuses on highly forest-related ecosystem services to assess production process-level risks, rather than broadly aggregating all ecosystem service dependency ratings.

Finally, we aggregate the production process-level dependency scores into the GICS industry level, which is the original classification used by ENCORE. We then use the industry crosswalk tables provided by ENCORE, and the ISIC-USSIC link table, to match the data with our sample at the 2-digit SIC level. After excluding financial firms, regulated utilities, and public administration, we ended up with 64 unique industry groups. We normalize the continuous dependency score into 0-5 scale, to be comparable to the ENCORE six-level materiality rating at the production process level.

Table 2 Panel C shows the summary statistics of the dependency score for each high-level SIC division at the firm level. The top three high-level SIC divisions with the highest average forest dependency scores are agriculture, forestry, and fishing (2.52), mining (2.31), and manufacturing (1.04). At the 2-digit SIC level, top five industries with the highest dependency score are forestry (5.0), food and kindred products (3.15), coal mining (2.79), agricultural production crops (2.71), and agriculture production livestock and animal specialties (2.71). Table 3 shows that the average dependency measure *Dependency* is 0.93 for the firm-year panel sample and 0.91 for the loan-level sample.

3 Empirical design

We begin by examining whether banks incorporate physical and transition risks associated with forest loss into loan pricing. Firms with higher dependence on forest-based inputs are presumed to face greater risk exposure when forest loss occurs in close proximity, with the nature of the risk shaped by the underlying cause of the loss. Specifically, fire-induced forest loss represents a realization of *physical risk*, as it can abruptly disrupt firms that rely on forests by unexpectedly removing raw materials essential to their production processes. Wildfires may also produce secondary effects—such as smoke damage or destruction of physical assets—that can impact a broader range of firms. However, these effects are typically shorter-lived and less directly tied to production activities. In contrast, human-induced forest loss may similarly reduce the availability of forest-based inputs, but it often stems from the firm's own actions, such as supply chain expansion or land-use change. Consequently, it exposes forest-dependent firms to *transition risks*, as the loss signals involvement in deforestation and environmental degradation. This increases the likelihood of regulatory scrutiny under current or anticipated deforestation-related policies. Thus, we estimate the following model specification at the loan level:

$$\mathrm{Yield\ spread}_{\mathrm{b,f,t}} = \beta_1 \mathrm{Dependency}_{\mathrm{i}} + \beta_2 \mathrm{Loss}_{\mathrm{f,t-1}} + \beta_3 \mathrm{Dependency}_{\mathrm{i}} \times \mathrm{Loss}_{\mathrm{f,t-1}} + \theta_1 (\mathrm{Loan\ ctrls})_{\mathrm{b,f,t}} + \theta_2 (\mathrm{Bank\ ctrls})_{\mathrm{b,t-1}} + \theta_3 (\mathrm{Firm\ ctrls})_{\mathrm{f,t-1}} + \mathrm{FE} + \epsilon_{\mathrm{b,f,t}}. \quad (1)$$

The dependent variable $Yield\ spread_{b,f,t}$ is "all-in-spread drawn" (AISD) divided by 100. $\mathrm{Dependency}_{\mathrm{i}}$ is the proxy for the levels of an industry's forest dependency, aggregated at the

2-digit SIC level. Alternatively, we also construct a country-weighted forest dependency measure, where industry dependency is weighted by country-year-level total forest loss, to account for heterogeneity in deforestation exposure across countries.[12] $Loss_{f,t-1}$ captures the total forest loss—both fire-induced and human-induced—within a 10-kilometer radius of a firm's headquarter in the previous year.[13] Given that transition risks related to deforestation regulation were relatively limited during most of our sample period (2002–2024), an insignificant effect of human-induced loss combined with a significant effect of fire-induced loss would suggest that observed pricing responses are driven primarily by physical risk. The coefficient β_3 captures the differential change in loan yield spreads for high forest-dependent firms relative to low forest-dependent firms in response to forest loss, enabling us to assess whether banks price risk based on firms' reliance on forest-related inputs.

The vector, FE, represents a set of fixed effects to account for unobserved heterogeneity. In our baseline specification, we include year fixed effects to control for time-varying macroeconomic conditions. We further incorporate high-level industry fixed effects (SIC division) to examine within-sector variation in loan pricing. To account for cross-border lending heterogeneity, we also include bank–firm country fixed effects, which control for differences in lending practices that may arise from country-level interactions between lenders and borrowers—such as variations in regulatory regimes, deforestation exposure, or credit market conditions. Loan-level controls include a set of dummy variables: *If secured loan*, *If*

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[12] We calculate the country-weighted dependency score as $\text{Dependency} \times (1 + \text{forest loss}_{c,t})$, accounting for the risks associated with forest loss at country-year level. Both the dependency and forest loss measures are normalized to 0-1, so that when the country has very low forest loss in a year, the base level of an industry's inherent forest dependency remains unaffected. And when the country-level forest loss is substantial, its impact on the weighted dependency score can reach a maximum of 2, doubling the magnitude of the original industry dependency.

[13] While using headquarters locations might introduce potential measurement errors when production sites are located in different regions, many studies employing this proxy argue that a substantial portion of firms' operations, business activities and employees are concentrated near their headquarters (e.g., Chaney et al. 2012, Korniotis and Kumar 2013, Barrot and Sauvagnat 2016, Tuzel and Zhang 2017, Huynh and Xia 2021). Thus, our setting assumes that forest loss around headquarters is both significant and economically relevant to the firm.

base prime, *If refinance*, *Repeated lending*, *Loan purpose*, *Log loan amount*, and *Log maturity*. Borrower-level controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating,* all lagged by one year. Lender-level controls include *Bank size*, also lagged by one year. The summary statistics for the variables are reported in Table 3. All variables are defined in Appendix Table A.1. $\epsilon_{b,f,t}$ is the error terms, clustered at the 2-digit SIC industry and year level to account for correlated shocks within industries over time.

Next, we examine whether banks increase lending rates in response to the rising transition risks from deforestation, using the introduction of the EUDR as a policy shock that amplifies such risks. A key distinction in deforestation regulation lies in the origin of forest loss—whether it stems from external shocks or firm-driven actions. Forest loss caused by natural events such as wildfires is typically viewed as beyond a firm's control and is therefore unlikely to trigger regulatory penalties. In contrast, deforestation resulting from firms' deliberate decisions—such as supply chain expansion or land-use change—is more likely to attract regulatory scrutiny and elevate transition risks, particularly for forest-dependent firms. Unlike voluntary sustainability initiatives, the EUDR imposes legally binding due diligence requirements, mandating that firms ensure their products are deforestation-free. The regulation applies not only to EU-based firms but also to those exporting to or importing into the EU, thereby extending transition risks beyond the EU's borders. Firms involved in the production or trade of commodities listed under the EUDR must comply with strict traceability obligations, including documenting supply chains back to their geographic origin.

The regulation went into force on June 29, 2023, with compliance deadlines set for medium and large firms by December 30, 2025, and for small and micro enterprises by June 30, 2026. Non-compliant firms will be subject to penalties under national legislation and the EUDR framework. To capture the period of heightened transition risk, we define the post-July 2019 period—marking the release of the EUDR legislative framework—as the onset of increasing regulatory pressure surrounding deforestation. This timing reflects the forward-looking nature of compliance obligations and the market's anticipation of enforcement risk. Hence, we have the following model specification at the loan level:

$$\begin{aligned}\mathrm{Yield\ spread}_{b,f,t} = {} & \beta_1 \mathrm{Dependency}_i + \beta_2 \mathrm{Loss}_{f,t-1} + \beta_3 \mathrm{Post\ EUDR}_t + \beta_4 \mathrm{Dependency}_i \times \\ & \mathrm{Loss}_{f,t-1} + \beta_5 \mathrm{Dependency}_i \times \mathrm{Post\ EUDR}_t + \beta_6 \mathrm{Loss}_{f,t-1} \times \mathrm{Post\ EUDR}_t + \\ & \beta_7 \mathrm{Dependency}_i \times \mathrm{Loss}_{f,t-1} \times \mathrm{Post\ EUDR}_t + \theta_1 (\mathrm{Loan\ ctrls})_{b,f,t} + \\ & \theta_2 (\mathrm{Bank\ ctrls})_{b,t-1} + \theta_3 (\mathrm{Firm\ ctrls})_{f,t-1} + \mathrm{FE} + \epsilon_{b,f,t}. \qquad (2)\end{aligned}$$

$\mathrm{Post\ EUDR}_t$ is a time indicator, defined as one for years following the release of the EU deforestation regulation framework in July 2019, and zero otherwise. $\mathrm{Loss}_{f,t-1}$ is the total area of forest loss—either fire-induced or human-induced—within a 10-kilometer radius of a firm's headquarters in the previous year. While fire-induced forest loss can be more exogenous to firms in the form of natural disasters, human-induced forest loss is primarily driven by commodity production and agricultural expansion, often reflecting intentional land-use change for economic purposes. If greater human-induced forest loss heightens a forest-dependent firm's exposure to transition risk under stringent regulations, β_7 is expected to be significantly positive. This would indicate that banks adjust loan pricing in anticipation of elevated compliance costs or reputational risks associated with environmentally harmful business practices.

4 Empirical results and discussions

4.1 Baseline results: forest loss and loan spreads

We begin by estimating equation (1) to test whether banks charge higher loan spreads to forest-dependent firms following nearby forest loss. Table 4 presents the results using two forest loss measures: *Fire loss*, the total area (km^2) of forest loss due to fire in the previous year, and *Anthropogenic loss*, the total area (km^2) of human-induced forest loss in the previous year. Column (1) reports the interaction between *Fire loss* and *Dependency*. The coefficient is positive and statistically significant at the 5% level, indicating that banks charge higher yield spreads to firms with greater forest dependency when fire-induced loss occurs nearby. For instance, at the sample mean of *Dependency* (0.9108), the interaction coefficient implies that an additional square kilometer of fire-induced forest loss is associated with a 15 bps increase in loan spreads.[14] In comparison, column (2) shows the interaction between *Anthropogenic loss* and *Dependency* is small in magnitude and statistically insignificant. Column (3) includes both *Fire loss* and *Anthropogenic loss* in the model, and the results remain unchanged. Together, these baseline findings suggest that banks differentiate between two types of forest loss, and adjust pricing primarily in response to unanticipated physical shocks from fire-induced forest loss.

[Table 4]

One potential concern with the baseline results is that variation in forest dependency may be driven by a small number of high-dependency industry divisions. Table 2 Panel C shows that the average dependency score in agriculture, forestry, and fishing is significantly higher than that of both mining (sample t-test mean difference = 0.167, standard error = 0.0168) and manufacturing (sample t-test mean difference = 1.418, standard error = 0.0298). However, forest dependency also exhibits meaningful within-industry variation. For instance, the dependency level ranges from 1.622 to 5 in agriculture, forestry, and fishing division with 0.932 standard deviation, which is higher than the mean value of construction division that ranks fourth overall. To account for this within-industry heterogeneity, column (4) includes industry fixed effects for the eight high-level SIC divisions. The interaction coefficient

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[14] The marginal effect of fire loss on loan spreads is increasing in firms' forest dependency. Given the coefficient on *Fire loss* is -0.235 and the interaction term is 0.425, the net effect of fire loss on yield spread is positive when *Dependency* exceeds 0.5529, which is closest to the industry *construction special trade contractors* (0.56). At the sample mean of *Dependency* (0.9108), the marginal effect is $-0.235 + 0.425 \times 0.9108 = 0.1516$.

decreases slightly from 0.424 to 0.415 with significance at the 5% level, suggesting that banks continue to price the risks of fire-induced loss even after taking into account the industry categories.

Another possibility is whether banks adjust their pricing of fire-induced forest loss based on borrowers' country-level deforestation risk. That is, even when firms share similar production processes and forest dependency, those located in countries with higher deforestation exposure may face steeper borrowing costs. To address this, column (5) employs a country-weighted dependency measure *Weighted dependency*, which gives higher weight to firms operating in high-deforestation risk countries. The interaction coefficient increases from 0.424 to 0.527, significant at the 5% level. This result suggests that banks are more sensitive to physical risk when it arises in higher-risk geographic contexts.

To further assess whether banks respond to the absolute magnitude of fire-induced loss across countries or just place greater weight on within-country variation, column (6) includes bank×firm country fixed effects. The interaction coefficient changes only modestly from 0.527 to 0.586 and remains statistically significant at the 5% level. This indicates that banks are more focused on relative differences in fire-induced loss within a given country rather than pricing based on cross-country comparisons. By comparing bank's lending behavior within specific borrower countries over time, the estimate captures how banks adjust loan pricing in response to actual fire loss near a borrower of a country, rather than merely accounting for the magnitude of the wildfire risk. In other words, being in a more wildfire-prone country does not necessarily means it will automatically face higher pricing in loan. Taken together with the findings from Column (5), the evidence implies that banks account for both the broader deforestation risk of a country and the localized realization of fire-induced loss.

One concern is whether the observed loan pricing effects are driven by general firm-level climate risks rather than the specific impact of forest loss. To address this, Table B.1

replicates the baseline results controlling for the climate risk index, proposed by Li et al. (2024), using the sample of U.S. listed firms. The specification includes controls for acute physical risk, chronic physical risk, and transition risk. After adding these controls, the interaction coefficient between *Dependency* and *Fire loss* declines only slightly from 0.587 to 0.584, with both estimates statistically significant at the 1% level. This minimal change suggests that the pricing effect is not primarily driven by broader climate risk exposure, but instead reflects the distinct influence of forest loss on firms with high forest dependency.

4.2 Robustness

For natural disasters like fire-induced forest loss, the severity of the event matters for financial risk assessment. Small fires may have limited economic consequences, but very large fires, despite their lower probability, are expected to cause substantial operational disruptions to firms reliant on forest resources. If banks perceive extreme fire-induced forest losses as disproportionately riskier than moderate ones, we should expect to see a nonlinear pattern in loan pricing. Table 5 investigates this by estimating equation (1) using the interaction between the equally distributed forest dependency groups and a list of fire-induced loss measures. To facilitate interpretation, we supplement the continuous variable *Fire loss* with a series of dummy variables representing percentile thresholds of fire-induced loss. The dependent variable is *Yield spread*. In all specifications, the forest dependency group variable is *High dependency*, defined as one if the firm's forest dependency score exceeds the sample median and zero otherwise.

[Table 5]

Column (1) reports that the interaction between *High dependency* and *Fire loss* is positively significant at the 5% level, with magnitude of 0.194, suggesting that a one-standard-deviation increase in fire-induced loss raises the yield spread by 2.4 bps for forest-dependent firms compared to other firms. A potential limitation is that this interpretation may understate the pricing effect of very large fire events, as the distribution of *Fire loss* can be right-skewed. As a result, the linear specification may not fully capture whether banks respond more aggressively when the fire-induced forest loss are particularly severe. To explore this possibility, we redefine fire-induced loss using discrete indicators for large events. Column (2) introduces a binary variable, *If fire*, equal to one if a firm experienced any non-zero fire-induced loss in the prior year, and zero otherwise. Its interaction coefficient with *High dependency* is 0.145, significant at the 5% level, suggesting that when a fire-induced loss event occurs (averagely 0.0111 km^2, around 2.08 football pitches), the yield spread difference between high and low forest dependency increases by 14.5 bps. Columns (3) to (6) extend this analysis using top-percentile cutoffs of 40%, 25%, 5%, and 3%, with interaction coefficients increasing as the fire severity threshold becomes more extreme.

Figure 2 plots the interaction coefficients between *High dependency* and the fire loss indicator, where large fire-induced loss events are defined using percentile cut-offs ranging from the 50^{th} to the 99^{th}. The figure shows a clear upward trend in the coefficients as the threshold for defining a large fire event becomes more extreme. Notably, when the fire loss exceeds the 95^{th} percentile, the upward trend gets steeper, highlighting a nonlinear relationship between fire severity and loan pricing. Across all specifications, the interaction terms remain statistically significant, with coefficients ranging from around 0.12 to 0.65.[15] These estimates suggest that when a fire-induced forest loss occurs, forest-dependent firms are charged between 12 and 65 bps more in yield spread compared to other firms, depending on the magnitude of the fire.

[Figure 2]

[15] The lowest coefficient is 0.1256, (standard error = 0.06235) at the 58^{th} percentile cut-off. The highest coefficient is 0.6576, (standard error = 0.1524) at the 99^{th} percentile cut-off.

4.3 Policy shock: the introduction of the EUDR

We next estimate equation (2) to assess whether banks increase yield spread in response to rising deforestation-related transition risks. Since compliance deadlines for medium and large firms are set for December 2025, the period from August 2019 to December 2024 is expected to reflect elevated transition risk for firms with forest-based production processes. Because the EUDR applies to all firms located in, operating within, or trading with the EU, we begin by estimating equation (2) using the full global sample.

Column (1) of Table 6 reports the results for the triple interaction among *Fire loss*, *Dependency*, and *Post EUDR*, a time indicator equal to one following the release of the EUDR framework in July 2019 and zero otherwise. The interaction between *Dependency* and *Fire loss* are positively significant, consistent with our baseline findings. The triple interaction is positively non-significant, indicating that banks do not alter their pricing of fire-induced loss for forest-dependent firms after the introduction of the EUDR framework. In column (2), we use *Weighted dependency* to account for country-year variation in deforestation exposure. The triple interaction term remains non-significant, consistent with the expectation that fire-induced forest loss is an exogenous event rather than a firm-driven activity, thereby not subject to heightened transition risk under the EUDR.

[Table 6]

In comparison, columns (3) and (4) of Table 6 repeat the analysis using *Anthropogenic loss* as the measure of deforestation exposure. In column (3), the triple interaction of *Dependency*, *Anthropogenic loss* and *Post EUDR* is 0.261, significant at the 10% level. This suggests that, after the EUDR framework was introduced, banks began to differentiate more between firms depending on how much their production relies on forest when those firms are exposed to human-driven deforestation. The estimated effect translates into an 8.1 basis point increase in yield spreads for a one-standard-deviation increase in both the dependency score and human-induced forest loss. In column (4), we use *Weighted dependency*, which adjusts for country-year variation in deforestation risk while maintaining the same scale. The coefficient on the triple interaction increases to 0.416 and is significant at the 5% level, indicating that after the EUDR framework was introduced, banks imposed larger pricing penalties on forest-dependent firms facing human-induced loss, particularly when those firms are located in countries with higher deforestation risk.

To examine how the pricing difference evolves as transition risks develop over time, Figure 3 plots the coefficients from estimating Equation (2) using a year-by-year rolling window, separately for fire-induced and human-induced forest loss. Following fire-induced loss, the yield spread difference between forest-dependent firms and other firms is non-significant in recent years, with wide fluctuations around zero, suggesting no clear trend. In contrast, the pricing effect following human-induced loss declines around the 2008 financial crisis but begins to rise steadily after 2016, coinciding with the adoption of the Paris Agreement in December 2015. The difference becomes statistically significant from 2020 onward, consistent with the timing of the European Commission's proposed deforestation regulation framework in July 2019.

[Figure 3]

4.3.1 Country heterogeneity

Given the differential pricing of transition risks after the introduction of the EUDR observed globally, a natural question is whether this effect is more pronounced for transactions within the EU. If a borrower is headquartered in the EU, it is reasonable to assume the firm operates within the region and is directly subject to the regulation, facing higher costs if it attempts to exit the EU market. For these firms, a stronger post-regulation pricing response by EU banks would suggest that these banks are more likely to internalize compliance considerations when setting loan terms. Table 7 investigates how the EUDR affects yield spreads across different borrower-lender country pairs. The empirical setup follows the previous section, with *Yield spread* as the dependent variable, *Dependency* measuring forest reliance, and *Anthropogenic loss* capturing human-driven deforestation. In column (1), the sample is restricted to loans where both the lead bank and the borrower are based in the EU. These firms are more likely to remain in the EU and face higher costs of relocation, making them more exposed to the full scope of the regulation. The triple interaction of *Dependency*, *Anthropogenic* and *Post EUDR* is 1.766 at the 5% significance level, and is significantly larger than the corresponding coefficient of 0.238 at the 1% level for the non-EU lending pair sample in column (2). These results suggest that EU banks impose substantially higher yield spreads on forest-dependent EU borrowers exposed to human-induced loss after the EUDR framework was introduced. In economic terms, the pricing gap between high- and low-dependency firms (relative to the sample median) ranges from approximately 40 to 200 bps depending on the level of human-induced loss, as shown in Figure 4.

[Table 7] [Figure 4]

We also assess whether the regulation's effects spill over to all OECD member countries. Column (3) shows a triple interaction coefficient of 0.438 for OECD lending pairs, which is about one-fourth the magnitude of the effect observed for EU pairs in column (1). The coefficient is significantly than the 0.124 coefficient larger at the 5% level for non-OECD lending pairs in column (4). While the pricing effect is weaker for all OECD lending pairs than that observed within the EU, the results suggest that loan pricing in OECD countries also exhibit sensitivity to deforestation-related regulatory developments in EU.

To further examine whether EU banks adopt a stronger compliance role than non-EU banks following the introduction of the EUDR framework, we restrict the borrower sample to EU operators. This ensures that all firms in the analysis are directly exposed to the elevated transition risk, as they place products in the EU market and are more likely to fall under the regulation's scope. We identify EU operators using Compustat Segment data to flag firms with major customers in the EU, and we also include firms headquartered in the EU, given their clear regulatory exposure. By focusing on firms likely to be directly affected by the EUDR, this approach enables a cleaner comparison between the lending behavior of EU and non-EU banks. Table B.2 reports the results. In column (1), the triple interaction term of *Dependency*, *Anthropogenic Loss*, and *Post EUDR* is positively significant at the 5% level, indicating that EU banks increase the yield spread for forest-dependent EU operators experiencing human-induced forest loss after the introduction of the EUDR. In contrast, column (2) finds no significant effect for non-EU banks, suggesting that their loan pricing is not responsive to the EUDR. Columns (3) and (4) extend the analysis using *Weighted dependency*, and continue to show a clear difference in how EU and non-EU banks adjust the yield spread toward EU operators.

Given that our sample covers multiple regulatory phases of the EUDR, we further examine how changes in regulatory certainty influence loan pricing. Between the EUDR framework proposal in July 2019 and its formal enforcement in June 2023, firms faced elevated transition risks driven by both anticipated compliance requirements and uncertainty about the timing and details of implementation. Once the regulation came into force, both the compliance requirements and the deadlines became clear. This shift removed ambiguity but increased pressure on firms, as they now faced a fixed timeline to complete the transition or face penalties for noncompliance. Table 8 investigates how banks respond to these changes by adjusting loan spreads. The dependent variable is *Yield spread*, and *Anthropogenic loss* captures exposure to human-induced deforestation. Columns (1) and (2) uses *Dependency* to measure forest dependency, and columns (3) and (4) uses *Weighted dependency* to account for the country-year-level forest loss risk. To distinguish the two regulatory phases, we define two time indicators: *Post EUDR (phase 1)* as equal to one for the period between the framework release and the regulation's entry into force (August 2019 to June 2023), and *Post EUDR (phase 2)* as equal to one for the period after enforcement begins.

[Table 8]

Column (1) reports the results for the sample of loans between EU banks and EU firms. The triple interaction coefficient among *Dependency*, *Anthropogenic* and *Post EUDR (phase 1)* is 2.26 at the 1% significance level. For phase 2, the coefficient rises to 4.608, also at the 1% significance level. Since the actual area of human-induced forest loss decreases over the regulation phases, we assess the economic significance using variations within these subsamples. This corresponds to a 43.5 bps difference in yield spread for phase 1 and 46.9 bps for phase 2 for a one-standard-deviation increase in both dependency score and human-induced loss. These results suggest that EU banks increasingly penalize forest-dependent EU firms following human-induced loss, especially as transition risks become more immediate in phase 2 of the regulation. Column (2) estimates the same specification for loans where either the lender or the borrower is outside the EU. The coefficients in both phases are small and not statistically significant, suggesting that the pricing response to the EUDR is concentrated in EU-based lending relationships. Columns (3) and (4) use *Weighted dependency* as forest dependency measure. After considering the country-level deforestation risk of borrowers, the triple interaction coefficients for EU pairs nearly double in both phases, and remain significantly different from those in non-EU pairs, reinforcing the view that EU banks play a stronger compliance role under the EUDR.

4.3.2 Firm heterogeneity: firm commitments on deforestation

We next examine whether this pricing effect is mitigated when firms actively engage with deforestation issues in their public disclosures. Table 9 presents the loan-level results testing whether firm-level commitments influence how banks price transition risks associated with deforestation. Again, the dependent variable is *Yield spread*, and the forest loss measure is *Anthropogenic loss*. We use the total number of corporate disclosures in the previous year that mention the term "deforestation" as a proxy for firm commitments (*Firm commit*).[16] The corporate filings are accessed via Refinitiv Advanced Filings Search (AdvFil), including ESG reports, annual reports, and SEC filings.

[Table 9]

Columns (1) and (2) use *Dependency* as the forest dependency measure and estimate the model separately for the pre- and post-EUDR periods. In the pre-EUDR subsample, the triple interaction among *Dependency*, *Anthropogenic loss*, and *Firm commit* is positive, small in magnitude, and statistically non-significant. In contrast, the same interaction in the post-EUDR subsample is negatively significant at the 5% level. When using *Weighted dependency* to adjust for country-year variation in deforestation risk, the difference in magnitude becomes even more pronounced. These results suggest that, after the EUDR framework, firms that actively disclose deforestation-related commitments are less penalized in loan pricing when exposed to human-induced forest loss. By signaling to lenders that they are addressing deforestation risks, these firms are able to soften the increase in yield spreads associated with the regulatory exposure.

5 Mechanisms and ex-post outcomes

5.1 Mechanism: forest loss and firm operation

To understand why banks impose higher costs for firms exposed to deforestation risk, we then examine whether large wildfires actually disrupt operations at forest-dependent firms while human-induced loss does not. If fire-induced loss events do not affect production, the

[16] The proxy relies on two key intuitions. First, the term "deforestation" is highly specific and almost exclusively used in environmental contexts, in contrast to broader terms like "ecosystem", which may appear in non-environmental discussions. Second, when firms mention deforestation in formal filings, they are typically acknowledging the issue or signaling actions to address it, rather than reporting that they are contributing to it.

observed pricing response may reflect perceived rather than realized physical risk. A potential underlying mechanism is that wildfires, as acute physical shocks, may disrupt operations by destroying the forest that these firms' production relies on. By contrast, human-induced forest loss often results from the firm's own managerial decisions such as business expansion, and is less likely to create unexpected operational disruption. To examine this, Table 10 presents difference-in-differences (DiD) estimates using the firm-year panel of DealScan sample. The dependent variable is operating cash flow scaled by tangible assets from the previous year. Firms are grouped using *Top dependency*, a dummy variable equals one if the firm's forest-dependency score is within top 30% of the sample, and zero if within bottom 30%. Columns (1) and (2) reports the interaction between *Top dependency* and *Post large fire loss*, which is defined as one if two years after a large wildfire event, and zero before an event. Columns (3) and (4) reports the interaction between *Top dependency* and *Post large anthropogenic loss*, which is defined as one if two years after a large human-induced forest loss event, and zero before an event.

[Table 10]

The interaction coefficient in column (1) shows that, in two years after a large fire-induced loss event, high-forest-dependent firms experience a 24.5% decline in operating cash flow relative to low-forest-dependent firms. Column (2) presents results from a dynamic specification. The negative impact is strongest in the first year after the fire, with a 29.3% decline significant at the 1% level, and diminishes to 22.1% in the second year, significant at the 10% level. In contrast, columns (3) and (4) show no significant effect of large human-induced forest loss on cash flow. This suggests that human-induced loss does not materialize as a physical disruption for forest-dependent firms. Rather than being an external physical shock, such deforestation is often a result of firm-initiated activities that do not appear to reduce short-term operational performance.

Figure 5 presents coefficient estimates from the dynamic DiD analysis over a broader window from two years before to four years after a large forest loss event. The top panel shows that, following a large fire-induced loss, the cash flow of high-forest-dependent firms declines significantly in the first year, partially recovers in the second year, and converges with the low-dependency group in later years. In contrast, the bottom panel shows no cash flow difference between high- and low-dependency firms immediately after a large human-induced loss. Over time, the gap widens in favor of the high-dependency group, suggesting that deforestation-related business expansion may begin to generate higher cash flows in subsequent years.

[Figure 5]

5.2 Ex-post outcome in production

After receiving syndicated loans, firms may adjust their production sourcing strategies and reforestation activities, offering insight into whether lending supports green transitions or reinforces deforestation-intensive operations. If a high-transition-risk firm reduces its deforestation exposure after securing loans, it suggests that the lenders play an engagement role in promoting sustainability. In contrast, if the firm continues operating with high deforestation intensity, it indicates that the loan might function as brown investment that enables continued unsustainable operations. We first examine changes in firms' forest-related supply following loan receipt.

Table 11 reports firm-level results on how receiving loans after forest loss affects a firm's supply chain. We use two outcome variables to capture different types of supply chain transitions: (1) *Supply dependency* measures the share of a firm's inputs sourced from forest-dependent suppliers, calculated as the sum of each supplier's *Dependency* weighted by its share of the firm's total purchases. A decline in this measure indicates a shift away from forest-based inputs, reflecting an overall transition in production sourcing. (2) *Country-adj supply* measures the share of inputs from forest-dependent suppliers located in high-deforestation-risk countries, calculated as the sum of each supplier's *Weighted dependency* (accounting for both forest dependency and country-level deforestation risk) multiplied by its share of the firm's total purchases. A decrease in this variable reflects a shift toward responsible sourcing, where the firm continues to use forest inputs but increasingly sources them from countries with lower deforestation risk. In both Panel A and Panel B, columns (1) and (3) report the average outcome over the next three years , while columns (2) and (4) use the four-year average. Firms are classified using *If get loan*, a dummy equal to one if a firm obtains a syndicated loan in the same year or within one year following a large forest loss, and zero otherwise.

[Table 11]

Panel A examines firm responses following large human-induced forest loss, where *Post large anthropogenic loss* is a time indicator equal to one for the three years following such large loss, and zero for three years before. In columns (1) and (2), the interaction between *If get loan* and *Post large anthropogenic loss* is negative and only significant at the 10% level for the outcome window of following three years. This suggests that firms receiving loans do not substantially reduce their overall reliance on forest-based inputs, indicating limited change in the structure of their production. In columns (3) and (4), the interaction terms are both negatively significant at the 5% level when the outcome is *Country-adj supply*. This indicates that, rather than cutting total forest input use, firms shift toward sourcing from countries with lower deforestation risk. In other words, when firms face heightened transition risk from large human-induced loss, receiving syndicated loans is associated with a shift toward more responsible sourcing instead of a broad retreat from forest-dependent inputs.

Panel B presents the outcomes after large fire-induced forest loss, using the same specifications and table structure as in Panel A. Here, *Post large fire loss* equals one for the three years after the loss event, and zero for the three years prior. Across columns (1) to (4), the interaction between *If get loan* and *Post large fire loss* is negative and statistically non-significant in all cases. This suggests that firms receiving loans do not significantly adjust their supply chain exposure to forest inputs in response to fire-induced loss, relative to firms that do not receive loans. The lack of response implies firms are less motivated to change their sourcing behavior, as forest fires are relatively exogenous and less likely to heighten the firms' exposure on transition risks.

5.3 Ex-post outcome in reforestation

Next, we examine whether firms that receive syndicated loans following large human-induced forest loss contribute to reforestation in the years that follow. Unlike supply chain adjustments which firms can manage through operational or sourcing decisions, the environmental damage caused by human-induced deforestation is long-lasting and irreversible without deliberate restoration. In other words, reforestation requires active engagement, and it cannot be undone passively or avoided through reallocation. To capture this activity, we use geospatial vegetation data surrounding firms as a proxy for reforestation. Table 12 presents the results from the firm-year panel, where the dependent variable is the Normalized Difference Vegetation Index (NDVI), a satellite-based measure of vegetation greenness from NASA MODIS. The time indicator is *Post large anthropogenic loss*, which equals one for the three years following a large human-induced forest loss and zero for the three years prior. The group indicator is *If get loan*, which is equal to one if a firm secures a syndicated loan in the same year or within one year after the forest loss event.

[Table 12]

Panel A reports the results for the full sample, while Panel B focuses on firms with forest dependency scores above the sample median. In Panel A, the interaction between *If get loan* and *Post large anthropogenic loss* is positive and significant across all forward-looking windows, with coefficients ranging from 1.174 (within one year after the event) to 1.215 (within two years), all significant at the 1% level. This suggests that firms securing loans after experiencing forest loss show increased *NDVI*, indicating a higher likelihood of reforestation efforts. Panel B restricts the analysis to firms with high forest dependency. The interaction terms remain positive and are larger in magnitude, ranging from 1.555 (within one year) to 1.595 (within three years), all significant at the 5% level. This indicates that forest-dependent firms are more likely to engage in reforestation efforts following loan receipt, suggesting a stronger response to transition risk when the firm's operations are more closely tied to forest.

To further examine our findings, we conduct a parallel analysis for fire-induced forest loss in Table B.3. Unlike human-driven loss, fire-induced loss reflects an acute physical shock rather than a consequence of firm activity. The results show no significant relationship between loan receipt and subsequent changes in *NDVI*, suggesting that reforestation efforts are not systematically associated with financing when forest loss is caused by wildfires. This reinforces the idea that post-loan reforestation is more likely to occur when deforestation is anthropogenic and potentially subject to regulatory scrutiny.

5.4 Ex-post outcome in pollutive plant divestiture

Firms may also respond to deforestation-related transition risks by adjusting their asset portfolios. One potential channel is the divestiture of pollutive forest-dependent plants, particularly if syndicated loan financing provides the capital needed to support a shift toward more sustainable operations. If firms use loans to facilitate such transition, we would expect an increase in the likelihood of divesting pollutive plants. Table 13 tests this hypothesis by examining whether firms that receive loans are more likely to divest pollutive forest-dependent plants in the years following large human-induced forest loss. The sample consists of U.S. public firms with at least one TRI-listed plant, and divestiture data are obtained from the SDC M&A database. To ensure meaningful asset ownership transfers, we restrict the sample to transactions in which the buyer acquires more than 50% ownership, and exclude financial firms as both acquirers and targets. Columns (1) to (3) examine divestitures of pollutive plants with nonzero forest dependency, while columns (4) to (6) focus on pollutive plants with forest dependency scores above the sample median. The divestiture indicator is scaled by 100, so estimated coefficients can be interpreted as percentage-point changes in the probability of divestiture.

[Table 13]

The results show that forest-dependent firms receiving loans after experiencing human-induced forest loss are significantly more likely to divest pollutive forest-dependent plants. In columns (1) to (3), the triple interaction of *Dependency*, *Anthropogenic loss*, and *If get loan* is positively significant at the 1% level across all time horizons, increasing from 1.095 in the subsequent two years to 1.215 over four years. Economically, the estimate in column (3) implies that a one-standard-deviation increase in both forest dependency and human-induced loss raises the likelihood of divestiture by 0.38 percentage points more for firms that receive loans than for those that do not within the four-year window. In columns (4) to (6), this effect persists and intensifies over the next three years when restricting the analysis to highly forest-dependent plants, suggesting a stronger divestiture response among firms with greater exposure to deforestation-related risks.

5.5 Further discussions: selection into loan receipt and alternative measures

A potential concern is that firms receiving loans may have different characteristics from those that do not, which might in turn influence their ex-post outcomes. To validate the effectiveness of *If get loan* as a group assignment indicator, we first assess whether loan receipt is associated with expanded debt capacity. Table B.4 reports that firms receiving a syndicated loan in a given year have a significantly higher book value of debt compared to non-recipients. We then examine whether firm characteristics predict loan receipt, which might introduce selection bias. Table B.5 reports estimates from a probit model of the likelihood of obtaining a syndicated loan. Column (3) shows that neither *Anthropogenic loss* nor *Dependency* significantly predicts loan receipt at the 5% level, suggesting that deforestation exposure does not systematically influence financing access. To further address potential selection concerns, Table B.6 includes the Inverse Mills Ratio (IMR) from the probit model into the analysis of post-loan production outcome, and the findings remain robust. Similarly, controlling for potential selection bias in loan receipt does not affect the results in reforestation (shown in Table B.7) and pollutive plant divestiture (shown in Table B.8).

Another concern is that MODIS NDVI might not be a direct measure of firms' actual engagement in reforestation projects. Besides, reforestation activities may not always occur near the firm's physical location but could instead be implemented elsewhere, such as through carbon offset projects. To address this limitation, we construct an alternative outcome measure based on firms' self-reported reforestation activities. We identify whether a firm engages in reforestation in a given year using a keyword dictionary derived from voluntary "Forestry & Land Use" carbon offset classifications.[17] These keywords are applied to firm-level disclosures collected from Refinitiv, including annual reports, ESG reports, SEC filings, press releases, etc. The outcome variable *Reforest* equals 100 if a firm explicitly reports reforestation activity within the estimation window following loan receipt.

Table B.9 shows that the results are consistent with previous findings. Forest-dependent firms receiving loans after human-induced forest loss are significantly more likely to engage in reforestation activities. Across all columns, the triple interaction of *Dependency*, *Anthropogenic loss*, and *If get loan* is positive and significant at the 1% level, with coefficients ranging from 0.560 to 0.756 over the four-year window. Economically, the estimate in Column (2) implies that a one-standard-deviation increase in both forest dependency and human-

[17] We construct the dictionary based on the categories of voluntary "Forestry & Land Use" projects documented in the Voluntary Registry Offsets Database (Haya et al. 2025). The dictionary includes terms related to key project types: afforestation, reforestation, (improved) forest management, (avoided) forest conversion, forest restoration, forest projects, (improved) grassland management, (avoided) grassland conversion, grassland restoration, (improved) wetland management, (avoided) wetland conversion, wetland restoration, and REDD+.

induced loss raises the likelihood of reforestation disclosure by 0.24 percentage points for firms that receive loans compared to those that do not. These results remain robust after accounting for potential selection into loan receipt, as shown in Table B.10.

6 Conclusion

This paper examines how banks price syndicated loans for firms exposed to deforestation risks, distinguishing between fire-induced and human-induced forest loss. We find that banks increase loan spreads for forest-dependent firms affected by fire-induced forest loss, charging a premium of 12-65 basis points. Regulatory frameworks, such as EUDR, have a profound influence on financial institutions' risk assessment and capital allocation. EU banks impose higher loan spreads on forest-dependent firms affected by human-induced loss compared to non-EU banks, with a stronger effect on firms operating within high-deforestation-risk countries. The regulatory impact extends to OECD countries, though with a lower intensity. Over different phases of EUDR implementation, loan pricing became more sensitive to transition risks from the policy framework proposal in July 2019 until the regulation's entry into force in June 2023, with a further rise afterwards.

We further find that firms also respond to the rising costs of capital and evolving regulations. Those that actively disclose deforestation-related risks experience reduced loan pricing penalties, demonstrating the role of transparency in mitigating financial burdens. In response to transition risks associated with human-induced forest loss, firms shift sourcing toward countries with lower deforestation risk, engage in reforestation efforts, and divest pollutive forest-dependent plants.

This study contributes to the literature by uncovering how banks integrate climate risks into loan pricing, highlighting the role of regulations in influencing capital markets, and providing firm-level evidence of regulatory-driven operational shifts.

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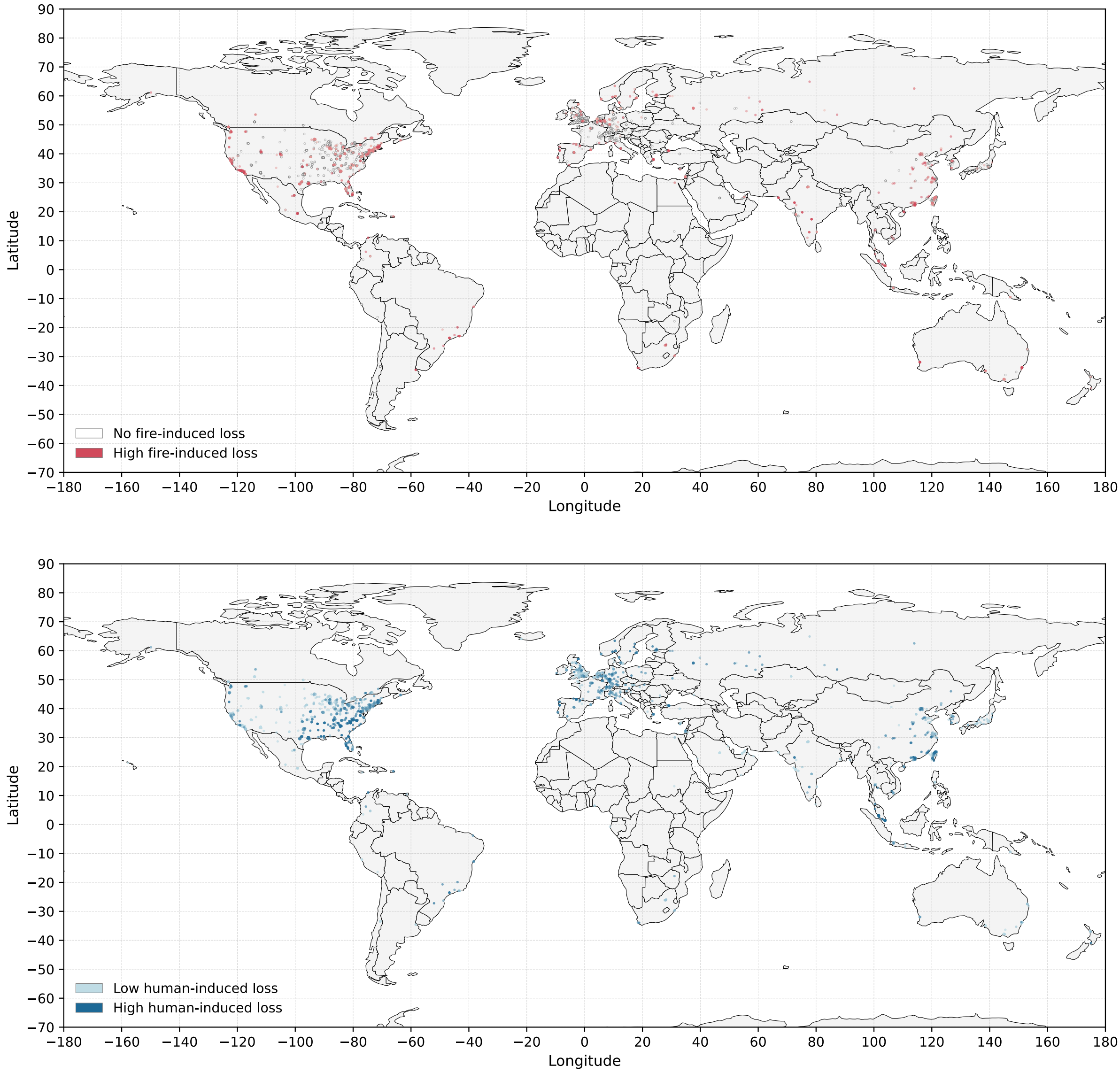


Figure 1. Forest loss of the sample firms in 2023

The plots illustrate the geographic distribution of our sample firms and the forest loss around them in 2023. The first figure depicts fire-induced forest loss, where gray circles indicate firms with no fire-induced loss, and increasing shades of red represent greater fire-induced loss. The second figure focuses on human-induced forest loss, with light blue circles indicating minimal forest loss and darker shades indicating more severe loss. The forest loss is measured within a 10km radius around each firm. The circles on the maps are visually enlarged to clearly display firms' locations, and do not represent the actual geographical areas of the forest loss.

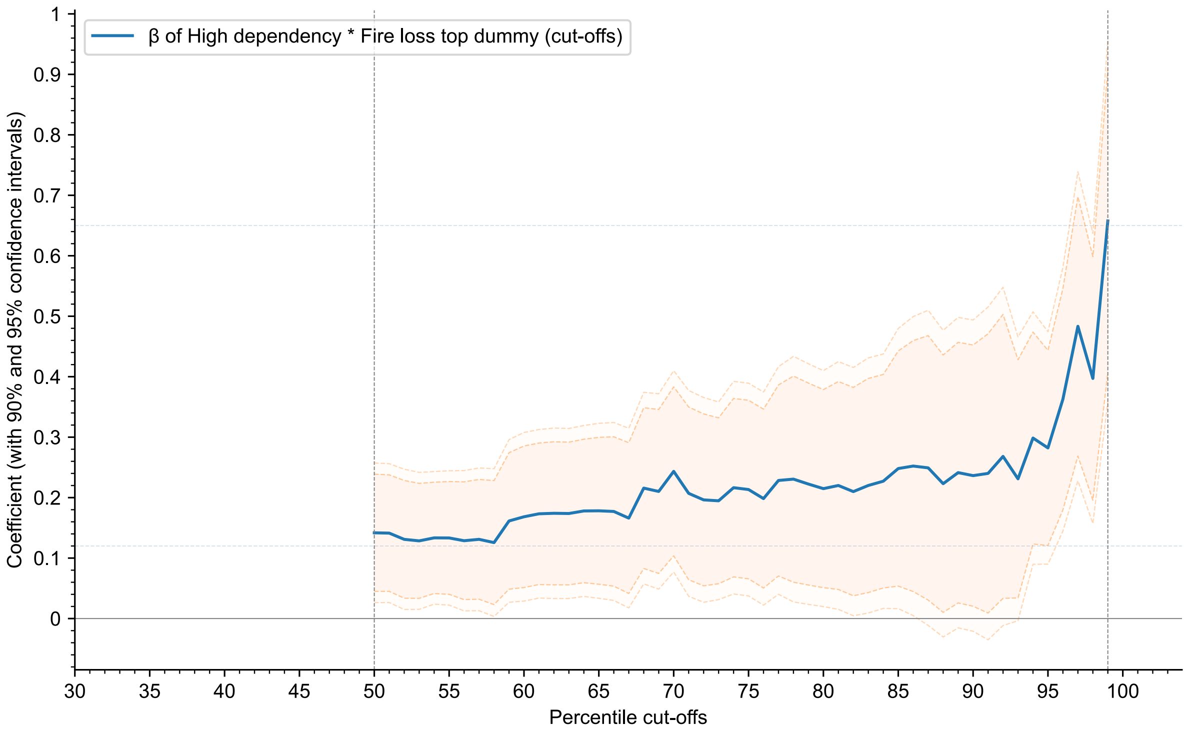
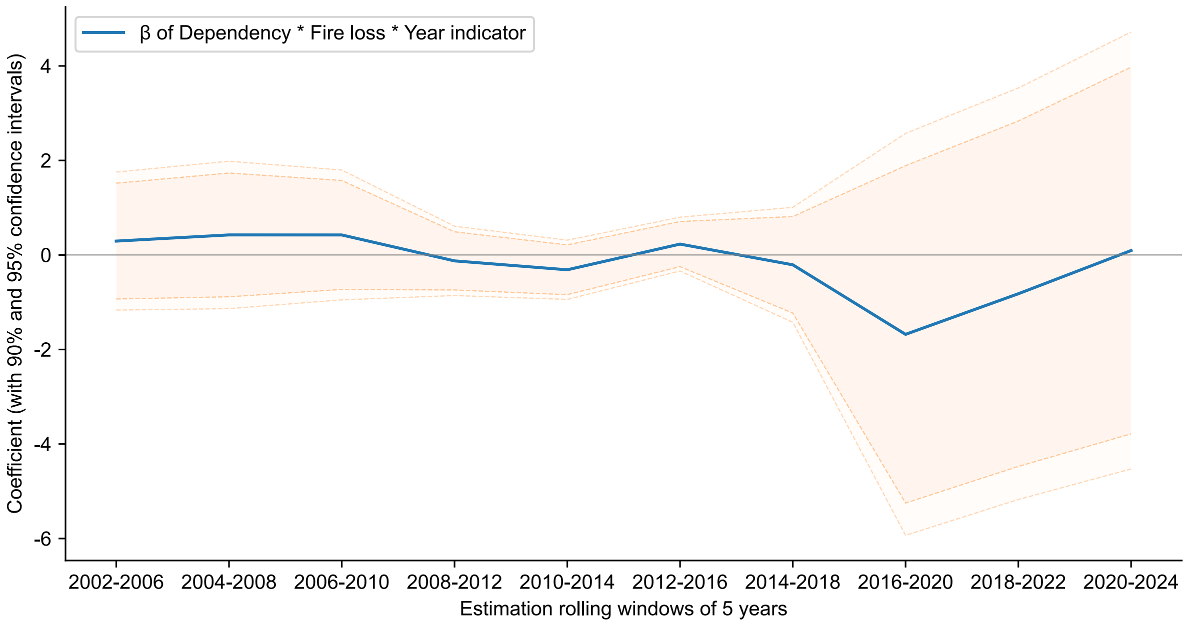


Figure 2. Fire-induced loss percentile cut-offs and yield spread

This figure plots the interaction coefficients between *High Dependency* and the fire-induced loss top percentile dummy, where the dependent variable is *Yield spread*. *High Dependency* equals one if the firm's forest dependency score is above the sample median, and zero if below. Each dummy captures whether the fire-induced forest loss falls above a given percentile threshold (e.g., top 25% when the cutoff is the 75th percentile), and is set to zero for firms experiencing no fire-related loss. The blue line displays the interaction coefficients across cutoffs. Shaded regions denote statistical significance: dark orange indicates significance at the 10% level; light orange at the 5% level.



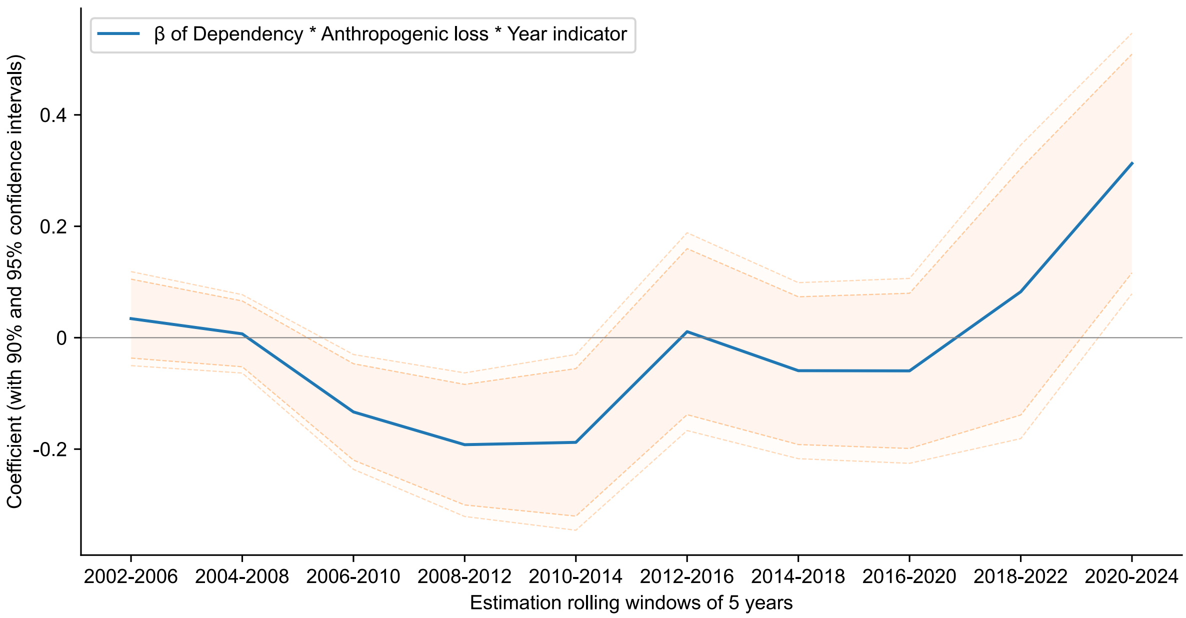


Figure 3. Year-by-year regression: Effect of forest loss on yield spread

This figure shows the interaction coefficients between firms' forest dependency score (*Dependency*), forest loss, and the estimation window time indicator in the loan-level test where yield spread is the dependent variable. The top figure shows fire-induced forest loss, while the bottom figure shows human-induced forest loss. The regressions are conducted year by year with a two-year interval from 2002 to 2020, using a rolling five-year estimation window to define the time indicator. For example, a value of 2020-2024 on the x-axis indicates that the time indicator used in the regression equals one from 2020 to 2024, and zero otherwise. The blue line represents the interaction coefficients. The dark orange area indicates significance at the 10% level, and the light orange area indicates significance at the 5% level.

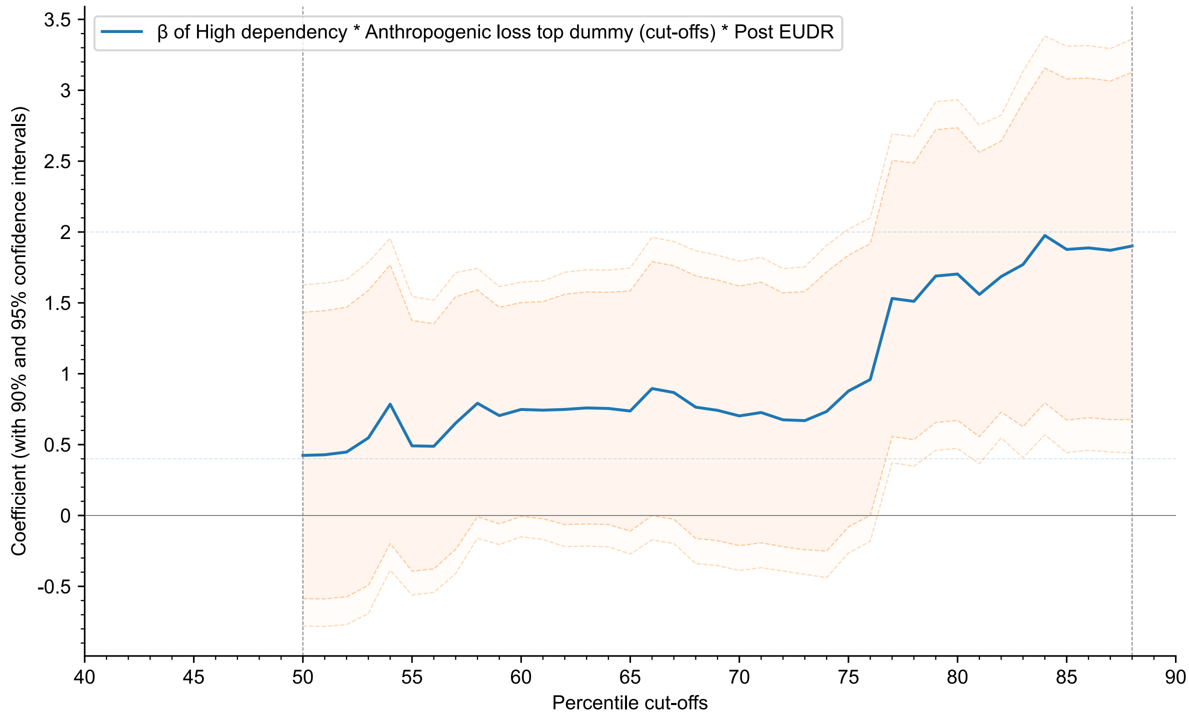


Figure 4. Human-induced loss percentile cut-offs and post-EUDR pricing

This figure plots the estimated coefficients on the triple interaction between *High Dependency*, human-induced loss top percentile dummy, and *Post EUDR*, where the dependent variable is *Yield spread*. The sample is restricted to EU bank-firm pairs, meaning both the lender and the borrower are headquartered in the EU. *High Dependency* equals one if the firm's forest dependency score is above the sample median, and zero if below. The human-induced loss top percentile dummy equals one if the borrower's exposure to human-induced forest loss exceeds a given percentile threshold, and zero if below the sample median. The blue line shows the triple interaction coefficients. Shaded areas indicate statistical significance: dark orange for the 10% level; light orange for the 5% level.

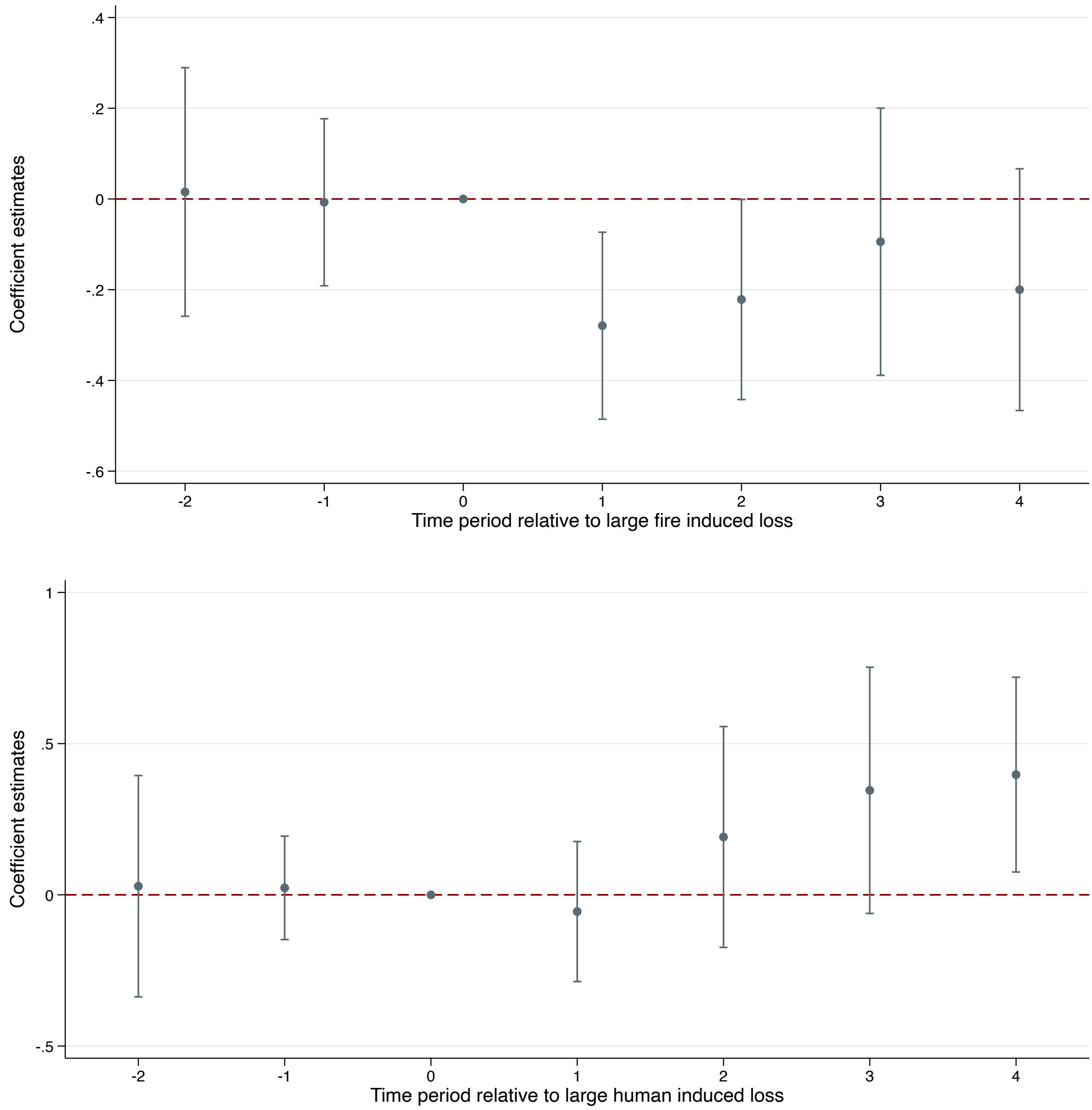


Figure 5. Dynamic effects of large forest loss on firm cash flow

This figure plots the time trend of the treatment effect estimates of firms' high forest-dependency on cash flow around large forest loss events. The top figure shows fire-induced forest loss, while the bottom figure shows human-induced forest loss. Cash flow is measured by dividing operating cash flow by the previous year tangible assets. Firms' dependency on forest is measured by *Top dependency*, a dummy variable equals one if the firm's forest-dependency score is within top 30% of the sample, and zero if within bottom 30%. For each period, we plot the point estimate (the solid circle) and the 90% confidence interval (the vertical lines intersecting the solid circles). Time indicators are defined for each year around a large forest loss event. For instance, Time (0) denotes the year of the large forest loss; Time (-1) denotes the year before the large forest loss, and so forth.

Table 1. Forest loss rankings across countries

This table reports the cross-country statistics of fire-induced forest loss (*Fire loss*) and human-induced forest loss (*Anthropogenic loss*) in square kilometers (km^2), in the firm-year panel sample. Panel A lists the top ten countries with the highest average fire-induced forest loss. Panel B lists the top ten countries with the highest average human-induced forest loss. The selection condition requires that each country has more than 100 firms in the sample.

Panel A. Top ten countries (>100 firms) with the highest average forest loss from fire

Fire loss	**Obs.**	**Mean**	**STD**	**Min**	**Median**	**Max**
Greece	428	0.3249	1.4402	0	0.00283	24.2641
Portugal	165	0.1275	0.5805	0	0.00631	5.1818
Russia	811	0.07622	1.1142	0	0.00713	31.4377
South Africa	343	0.06176	0.3540	0	0.00545	5.7976
Australia	2,682	0.04276	0.0868	0	0.01562	1.7574
Colombia	151	0.04008	0.09676	0	0.00779	0.7654
United States	40,255	0.02335	0.7545	0	0.00075	96.6292
Italy	882	0.01755	0.2124	0	0	4.1066
Brazil	803	0.01571	0.08534	0	0.00248	2.0665
Mexico	895	0.01562	0.02622	0	0.00422	0.1647

Panel B. Top ten countries (>100 firms) with the highest average human-induced forest loss

Anthropogenic loss	**Obs.**	**Mean**	**STD**	**Min**	**Median**	**Max**
Malaysia	502	1.3599	1.3103	0.03571	0.9703	11.4485
Portugal	165	0.7898	1.1001	0.0049	0.2370	5.2686
Finland	540	0.5442	0.6275	0.01819	0.3229	4.1991
Spain	1,369	0.4701	1.1811	0	0.08622	9.9872
Norway	670	0.4691	0.5331	0	0.3549	3.6835
Singapore	999	0.4597	0.5784	0.00626	0.2681	5.3275
Sweden	1,002	0.3886	0.7078	0	0.2161	6.2322
Poland	128	0.3885	0.5769	0	0.1543	3.1312
Turkey	370	0.3588	0.5463	0	0.1488	4.3528
Vietnam	157	0.3437	1.1123	0	0.02197	7.0750

Table 2. Industry rankings for forest loss and dependency

This table reports the descriptive statistics and the high-level SIC division rankings for fire-induced forest loss (*Fire loss*), human-induced forest loss (*Anthropogenic loss*), and forest dependency score (*Dependency*) in the firm-year level panel sample. Panel A provides details on *Fire loss*, Panel B focuses on *Anthropogenic loss*, and Panel C on *Dependency*.

Panel A. Industry rankings of the forest loss from fire

Fire loss	**Obs.**	**Mean**	**STD**	**Min**	**Median**	**Max**
Wholesale Trade	4,430	0.05306	2.0547	0	0.00067	96.6292
Construction	3,385	0.03250	0.4782	0	0.00034	20.1115
Services	18,031	0.01665	0.2528	0	0.0007	16.8422
Retail Trade	6,485	0.01534	0.2957	0	0.00071	16.8789
Agriculture, Forestry, Fishing	560	0.01428	0.0940	0	0.00071	1.5693
Transp. & Comm., Electric, Gas	12,675	0.01392	0.2484	0	0.00055	24.2641
Mining	8,631	0.01341	0.0974	0	0.00073	3.6712
Manufacturing	46,464	0.01067	0.2572	0	0.00059	31.4377

Panel B. Industry rankings of the human-induced forest loss

Anthropogenic loss	**Obs.**	**Mean**	**STD**	**Min**	**Median**	**Max**
Mining	8,631	0.2151	0.6158	0	0.04281	7.0488
Construction	3,385	0.2057	0.5824	0	0.0433	9.1428
Retail Trade	6,485	0.1984	0.4884	0	0.04472	7.7134
Wholesale Trade	4,430	0.1980	0.4576	0	0.04742	6.8372
Agriculture, Forestry, Fishing	560	0.1974	0.5211	0	0.04088	4.6086
Manufacturing	46,464	0.191	0.4959	0	0.04687	18.2719
Services	18,031	0.1788	0.4794	0	0.04317	20.0675
Transp. & Comm., Electric, Gas	12,675	0.1673	0.4404	0	0.03463	6.8476

Panel C. Firm-level summary of industry rankings of the dependency score

Dependency	**# of firms**	**Mean**	**STD**	**Min**	**Median**	**Max**
Agriculture, Forestry, Fishing	34	2.5188	0.9322	1.6228	2.693	5
Mining	560	2.3089	0.3264	1.7654	2.4649	2.7719
Manufacturing	2,730	1.039	0.7062	0.2281	0.8421	3.1316
Construction	203	0.8503	0.0726	0.5614	0.8684	0.8684
Services	1,265	0.5636	0.3199	0.114	0.7735	1.8041
Retail Trade	430	0.5548	0.1823	0.3596	0.5044	0.9561
Transp. & Comm., Electric, Gas	785	0.4999	0.5584	0	0.152	1.5298
Wholesale Trade	274	0.3395	0.0022	0.3377	0.3377	0.3421

Table 3. Summary statistics

This table reports the summary statistics of our main analysis sample at firm-year level and loan level. The definition of variables is detailed in Appendix Table A.1.

Variable	Obs.	Mean	STD	Min	Median	Max
Firm-year panel data						
Dependency	100,874	0.9349	0.744	0	0.7735	5
Weighted dependency	100,874	0.6025	0.5144	0	0.4468	5
Fire loss (km^2)	100,874	0.0153	0.4991	0	0.0007	96.6292
Anthropogenic loss (km^2)	100,874	0.1884	0.5025	0	0.043	20.0675
Cash flow	100,874	0.6335	1.3772	-2.25	0.283	6.5257
Total assets (m$)	100,874	117,382.02	379,342.96	0.246	3,860.5775	1,846,191.1
Firm size	100,874	8.4905	2.5819	0.2199	8.2588	14.4286
Leverage	100,874	0.5862	0.2463	0.0276	0.5845	3.0809
Loan level data						
All in spread drawn bps	42,590	191.666	146.5982	15	150	825
Yield spread	42,590	1.9167	1.466	0.15	1.5	8.25
Dependency	42,590	0.9108	0.7472	0	0.7735	5
Weighted dependency	42,590	0.5852	0.5268	0	0.4517	3.8872
Fire loss (km^2)	42,590	0.0077	0.1228	0	0.0007	11.8811
Anthropogenic loss (km^2)	42,590	0.1696	0.4197	0	0.0461	10.2686
Loan amount (m$)	42,590	645.9761	1,021.1591	2.5	250	5,000
Log loan amount	42,590	5.4331	1.5737	0.9163	5.5215	8.5172
Maturity (month)	42,590	54.6548	25.7748	3	60	222
Log maturity	42,590	3.8587	0.6031	1.0986	4.0943	5.4027
If secured loan	42,590	0.3731	0.4836	0	0	1
If base prime	42,590	0.0069	0.0827	0	0	1
If refinance	42,590	0.1719	0.3773	0	0	1
Repeated lending	42,590	0.395	0.4889	0	0	1
Loan purpose	42,590	0.2276	0.4193	0	0	1
Bank total assets (m$)	42,590	111,081.01	219,229.38	0.4038	3,578.467	2,608,333.8
Bank size	42,590	9.1003	2.976	0.3392	8.183	14.7742
Total assets (m$)	42,590	114,271.17	363,745.55	0.246	6,889.5908	1,846,191.1
Firm size	42,590	8.9617	2.3658	0.2199	8.8379	14.4286
Leverage	42,590	0.6131	0.2286	0.0276	0.6046	3.0809
ROA	42,590	0.0459	0.1119	-3.2236	0.0451	0.252
Liquidity	42,590	0.0886	0.088	0	0.0618	0.8015
Credit rating	42,590	5.6283	18.7277	0	0	98
Log credit rating	42,590	0.6205	1.2075	0	0	4.5951

Table 4. Forest loss and loan spreads

This table reports the baseline results of loan-level tests examining how forest loss affects yield spreads differently for firms based on their forest dependency. The dependent variable is *Yield spread*, measured by AISD divided by 100. Columns (1) to (4) use *Dependency* to measure forest dependency at the 2-digit SIC level, and columns (5) to (6) use *Weighted dependency*, which adjusts for risks associated with country-year-level forest loss and is rescaled to a range of 0 to 5. *Fire loss* refers to firm-level forest loss from fire in the previous year, and *Anthropogenic loss* refers to firm-level forest loss from human activities in the previous year. Column (4) includes high-level industry fixed effects at the high-level SIC division level, and column (6) includes bank×firm country-level fixed effects. Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC level and year level, with values reported in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Yield spread						
Dependency measures	*Dependency*				*Weighted dependency*	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependency measure	-0.00745	-0.00484	-0.00721	0.0000886	0.0703	-0.0359
	(0.0740)	(0.0761)	(0.0758)	(0.0476)	(0.103)	(0.0605)
Fire loss	-0.235*		-0.238*	-0.246*	-0.238	-0.327*
	(0.134)		(0.136)	(0.129)	(0.143)	(0.165)
Anthropogenic loss		0.0349	0.0373	0.0570	0.0574	0.0265
		(0.0439)	(0.0432)	(0.0355)	(0.0480)	(0.0295)
Dependency measure×	0.425**		0.424**	0.415**	0.527**	0.586**
Fire loss	(0.176)		(0.183)	(0.177)	(0.230)	(0.261)
Dependency measure×		0.00219	-0.00143	-0.0115	-0.0330	-0.0140
Anthropogenic loss		(0.0279)	(0.0288)	(0.0278)	(0.0377)	(0.0290)
If secured loan	0.683***	0.682***	0.682***	0.665***	0.680***	0.683***
	(0.0764)	(0.0766)	(0.0767)	(0.0714)	(0.0764)	(0.0560)
If base prime	1.038***	1.035***	1.036***	1.013***	1.026***	1.266***
	(0.207)	(0.209)	(0.209)	(0.226)	(0.204)	(0.277)
If refinance	-0.137*	-0.136*	-0.137*	-0.132*	-0.135*	-0.0896
	(0.0784)	(0.0782)	(0.0786)	(0.0746)	(0.0785)	(0.0555)
Repeated lending	-0.261***	-0.262***	-0.262***	-0.247***	-0.261***	-0.0888***
	(0.0468)	(0.0467)	(0.0469)	(0.0455)	(0.0466)	(0.0232)
Log loan amount	-0.0500	-0.0500	-0.0498	-0.0764**	-0.0519	-0.166***
	(0.0366)	(0.0367)	(0.0366)	(0.0323)	(0.0362)	(0.0148)
Log maturity	0.129**	0.130**	0.129**	0.129***	0.135***	0.127***
	(0.0479)	(0.0478)	(0.0478)	(0.0453)	(0.0474)	(0.0343)
Loan purpose	0.659***	0.660***	0.660***	0.665***	0.664***	0.523***
	(0.0741)	(0.0740)	(0.0740)	(0.0721)	(0.0747)	(0.0478)
Firm size	-0.155***	-0.155***	-0.154***	-0.145***	-0.154***	-0.0956***
	(0.0217)	(0.0217)	(0.0217)	(0.0183)	(0.0212)	(0.0137)
Leverage	0.950***	0.949***	0.950***	0.933***	0.965***	0.709***
	(0.163)	(0.163)	(0.163)	(0.155)	(0.164)	(0.104)
ROA	-1.138***	-1.142***	-1.141***	-1.060***	-1.135***	-1.241***
	(0.224)	(0.224)	(0.224)	(0.213)	(0.229)	(0.219)
Liquidity	-0.635***	-0.632***	-0.631***	-0.478***	-0.604**	-0.424*
	(0.217)	(0.216)	(0.217)	(0.151)	(0.220)	(0.230)
Log credit rating	0.0401***	0.0400***	0.0396***	0.0414**	0.0380**	0.00920
	(0.0141)	(0.0139)	(0.0139)	(0.0150)	(0.0136)	(0.0168)

Bank size	0.00918	0.00872	0.00876	0.00758	0.00781	-0.00479
	(0.0104)	(0.0105)	(0.0105)	(0.0102)	(0.0104)	(0.0133)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
High-level industry FE	No	No	No	Yes	No	No
Bank×firm country FE	No	No	No	No	No	Yes
Observations	42,590	42,590	42,590	42,590	42,590	42,590
Adjusted R-squared	0.342	0.341	0.342	0.357	0.342	0.515

Table 5. Forest loss and loan spreads: Fire cut-offs

This table reports the loan-level results with the interaction between the equally distributed forest dependency groups and the fire-induced loss measures, to further examine the loan pricing effects between high versus low forest-dependency groups following fire-induced forest loss. The dependent variable is *Yield spread*, measured by AISD divided by 100. Forest dependency group is separated by *High dependency*, defined as one if the firm's dependent score is above the sample median and zero otherwise. Column (1) uses *Fire loss* as the loss measure, which is the firm-level forest loss from fire in the previous year in km². Column (2) uses *If fire*, which equals one if a firm has non-zero fire-induced loss in the previous year, and zero otherwise. Columns (3) to (6) defines the top fire loss indicators based on percentile cut-offs of top 40%, 25%, 5%, and 3%, respectively, to compare with situations of no fire loss. Loan controls include *If secured loan, If base prime, If refinance, Repeated lending, Loan purpose, Log loan amount, and Log maturity*. Borrower controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. Lender controls include *Bank size*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Yield spread						
Fire measure	*Fire loss*	*If fire*	*Top 40%*	*Top 25%*	*Top 5%*	*Top 3%*
	(1)	(2)	(3)	(4)	(5)	(6)
High dependency	-0.214**	-0.291**	-0.291**	-0.295**	-0.289**	-0.286**
	(0.0972)	(0.121)	(0.121)	(0.121)	(0.120)	(0.120)
Fire measure	-0.0422	-0.0417	-0.0304	-0.0252	0.0504	-0.0741
	(0.0484)	(0.0571)	(0.0698)	(0.0775)	(0.0402)	(0.0585)
High dependency × Fire measure	0.194**	0.145**	0.165**	0.211**	0.298***	0.499***
	(0.0924)	(0.0596)	(0.0718)	(0.0892)	(0.102)	(0.136)
Statistics: fire loss cut-off group						
Mean (km^2)		0.01113	0.02763	0.04315	0.18511	0.28869
Equivalent # of football pitches		2.08	5.16	8.07	34.60	53.96
Standard deviation		0.1955	0.3084	0.3893	0.8558	1.0917
# of firm-year loss cases		23,411	17,977	10,922	2,004	1,221
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,590	42,590	37,136	30,065	21,125	20,342
Adjusted R-squared	0.346	0.347	0.344	0.345	0.335	0.331

Table 6. Transition risks from deforestation regulation change in the EU

This table presents loan-level regression results examining how the development of EUDR affects yield spreads for forest-dependent firms versus other firms when forest loss occurs. The dependent variable is *Yield spread*. All columns use *Dependency* to measure forest dependency at the 2-digit SIC level. Columns (1) and (2) use *Fire loss* as the loss measure, which is the firm-level forest loss from fire in the previous year. Columns (3) and (4) use *Anthropogenic loss*, which is the firm-level forest loss from human activities in the previous year. *Post EUDR* is a time indicator, defined as one after the deforestation framework stage (July 2019), and zero otherwise. Loan controls include *If secured loan, If base prime, If refinance, Repeated lending, Loan purpose, Log loan amount, and Log maturity*. Borrower controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. Lender controls include *Bank size*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Yield spread				
Loss measure	*Fire loss*		*Anthropogenic loss*	
	(1)	(2)	(3)	(4)
Dependency	-0.0257		-0.0194	
	(0.0721)		(0.0756)	
Weighted dependency		0.0469		0.0599
		(0.0980)		(0.104)
Loss measure	-0.249	-0.241	0.0622	0.0818
	(0.147)	(0.150)	(0.0508)	(0.0532)
Post EUDR	0.0115	0.0558	0.0946	0.148
	(0.110)	(0.110)	(0.140)	(0.143)
Dependency×Loss measure	0.455**		-0.0184	
	(0.202)		(0.0374)	
Weighted dependency×Loss measure		0.551**		-0.0519
		(0.248)		(0.0427)
Dependency×*Post EUDR*	0.186**		0.148	
	(0.0839)		(0.0929)	
Weighted dependency×*Post EUDR*		0.224		0.156
		(0.132)		(0.157)
Loss measure×*Post EUDR*	0.285	0.704	-0.415**	-0.424**
	(1.607)	(1.711)	(0.159)	(0.154)
Dependency×Loss measure×*Post EUDR*	-0.588		0.261*	
	(2.136)		(0.126)	
Weighted dependency×Loss measure×*Post EUDR*		-1.554		0.416**
		(3.066)		(0.185)
Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
Lender Controls	Yes	Yes	Yes	Yes
Observations	42,590	42,590	42,590	42,590
Adjusted R-squared	0.342	0.343	0.343	0.343

Table 7. Country heterogeneity of EUDR's effect on yield spreads

This table reports the loan-level results examining the country heterogeneity of the effect of the introduction of EUDR on yield spread differently for forest-dependent firms and other firms when human-induced loss occurred. The dependent variable is *Yield spread*. All columns use *Dependency* to measure forest dependency at the 2-digit SIC level, and use *Anthropogenic loss*, which is the firm-level forest loss from human activities in the previous year. *Post EUDR* is a time indicator, defined as one after the deforestation framework stage (July 2019), and zero otherwise. Columns (1) and (2) compare pairs of EU banks with EU firms versus other lending situations. Columns (3) and (4) compare pairs of OECD banks and firms versus other situations. Loan controls include *If secured loan, If base prime, If refinance, Repeated lending, Loan purpose, Log loan amount, and Log maturity*. Borrower controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. Lender controls include *Bank size*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Yield spread				
Bank country – Firm country pair	*EU*	*Non-EU*	*OECD*	*Non-OECD*
	(1)	(2)	(3)	(4)
Dependency	-0.125**	-0.00149	-0.0441	-0.0113
	(0.0553)	(0.0786)	(0.0450)	(0.0905)
Anthropogenic loss	0.129	0.0502	0.0380	0.0613
	(0.204)	(0.0439)	(0.0298)	(0.251)
Post EUDR	0.469***	0.0770	0.167	-0.198
	(0.154)	(0.140)	(0.108)	(0.124)
Dependency × Anthropogenic loss	-0.0239	-0.0224	0.000656	-0.0913
	(0.184)	(0.0315)	(0.0218)	(0.190)
Dependency × *Post EUDR*	0.0324	0.141	0.124	0.208
	(0.128)	(0.0973)	(0.0986)	(0.177)
Anthropogenic loss × *Post EUDR*	-1.751*	-0.376**	-0.633***	-0.154
	(0.846)	(0.171)	(0.205)	(0.400)
Dependency × Anthropogenic loss × *Post EUDR*	1.766**	0.238*	0.438***	0.124
	(0.712)	(0.134)	(0.142)	(0.263)
Chi-square test	*(1) = (2)*	10.1141***	*(3) = (4)*	6.1754**
P-value		0.0015		0.013
Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
Lender Controls	Yes	Yes	Yes	Yes
Observations	5,518	37,072	28,661	13,929
Adjusted R-squared	0.477	0.337	0.433	0.195

Table 8. EU deforestation regulation: Phase 1 and 2

This table reports the results examining the effects of different phases of EUDR on yield spread for forest-dependent firms and other firms when human-induced loss occurred. The dependent variable is *Yield spread*. Columns (1) and (2) use *Dependency* to measure forest dependency, and columns (3) and (4) use *Weighted dependency* to account for country-year-level forest loss risk. *Post EUDR (phase 1)* is the time indicator defined as one for the period between the deforestation policy framework and the regulation's entry into force (June 2023), and zero otherwise. *Post EUDR (phase 2)* is the time indicator defined as one after the EUDR goes into force, and zero otherwise. Columns (1) and (3) examine pairs of EU banks with EU firms, and Columns (2) and (4) examine other lending situations. Loan controls include *If secured loan, If base prime, If refinance, Repeated lending, Loan purpose, Log loan amount, and Log maturity*. Borrower controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. Lender controls include *Bank size*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Yield spread				
Dependency measure	*Dependency*		*Weighted dependency*	
Bank country – Firm country pair	*EU*	*Non-EU*	*EU*	*Non-EU*
	(1)	(2)	(3)	(4)
Dependency measure	-0.124**	-0.00149	-0.233**	0.0829
	(0.0581)	(0.0791)	(0.111)	(0.103)
Anthropogenic loss	0.133	0.0504	0.137	0.0672
	(0.206)	(0.0444)	(0.206)	(0.0495)
Post EUDR (phase 1)	0.606**	0.0663	0.596**	0.122
	(0.224)	(0.163)	(0.228)	(0.162)
Post EUDR (phase 2)	2.001***	0.552***	1.991***	0.580***
	(0.173)	(0.131)	(0.172)	(0.112)
Dependency measure×Anthropogenic loss	-0.0283	-0.0224	-0.0592	-0.0524
	(0.186)	(0.0321)	(0.350)	(0.0379)
Dependency measure×*Post EUDR (phase 1)*	-0.145	0.157	-0.250	0.169
	(0.302)	(0.116)	(0.582)	(0.192)
Dependency measure×*Post EUDR (phase 2)*	-0.261***	0.0454	-0.499***	0.0323
	(0.0820)	(0.119)	(0.154)	(0.165)
Anthropogenic loss×*Post EUDR (phase 1)*	-1.975***	-0.426*	-1.947***	-0.412*
	(0.681)	(0.248)	(0.675)	(0.216)
Anthropogenic loss×*Post EUDR (phase 2)*	-10.58***	-0.355	-10.53***	-0.360
	(1.791)	(0.286)	(1.813)	(0.319)
Dependency measure×Anthropogenic loss×	2.260***	0.288	4.201***	0.407
Post EUDR (phase1)	(0.642)	(0.195)	(1.205)	(0.255)
Dependency measure×Anthropogenic loss×	4.608***	0.186	8.662**	0.333
Post EUDR (phase 2)	(1.608)	(0.113)	(3.112)	(0.251)
Chi-square test (phase 1)	*(1) = (2)*	4.3247**	*(3) = (4)*	4.5246**
P-value		0.0376		0.0334
Chi-square test (phase 2)	*(1) = (2)*	15.8962***	*(3) = (4)*	15.1829***
P-value		0.0001		0.0001
Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
Lender Controls	Yes	Yes	Yes	Yes
Observations	5,518	37,072	5,518	37,072
Adjusted R-squared	0.481	0.338	0.481	0.338

Table 9. Firm commitments on deforestation

This table presents loan-level regression results examining how firm commitments on deforestation affect yield spreads for forest-dependent firms versus other firms when human-induced forest loss occurs. The dependent variable is *Yield spread*. Columns (1) and (2) use *Dependency* as the forest dependency measure, and Columns (3) and (4) use *Weighted dependency* to account for risks associated with country-year-level forest loss. Columns (1) and (3) report the results in subsample period before the deforestation framework stage, and columns (2) and (4) report the results in subsample period after. *Anthropogenic loss* is the firm-level forest loss from human activities in the previous year. *Firm commit* is the total number of firm disclosures that mentioned "deforestation" in the previous year. Loan controls include *If secured loan, If base prime, If refinance, Repeated lending, Loan purpose, Log loan amount, and Log maturity*. Borrower controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. Lender controls include *Bank size*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Yield spread				
Dependency measure	*Dependency*		*Weighted dependency*	
Subsample period	*Pre-EUDR*	*Post-EUDR*	*Pre-EUDR*	*Post-EUDR*
	(1)	(2)	(3)	(4)
Dependency measure	-0.0188	0.175	0.0662	0.237
	(0.0765)	(0.131)	(0.106)	(0.194)
Anthropogenic loss	0.0672	-0.316*	0.0879*	-0.294*
	(0.0478)	(0.136)	(0.0500)	(0.141)
Firm commit	-0.596	0.294	-0.560*	0.323
	(0.361)	(0.493)	(0.319)	(0.491)
Dependency measure×Anthropogenic loss	-0.0192	0.222*	-0.0551	0.316*
	(0.0362)	(0.0935)	(0.0418)	(0.149)
Dependency measure×*Firm commit*	0.160	-0.328	0.221	-0.485
	(0.228)	(0.163)	(0.292)	(0.275)
Anthropogenic loss×*Firm commit*	-0.104	1.173***	-0.128	1.256**
	(0.523)	(0.262)	(0.609)	(0.382)
Dependency measure× Anthropogenic loss×	0.349	-1.113**	0.601	-2.273*
Firm commit	(0.634)	(0.368)	(1.249)	(0.989)
Chi-square test	*(1) = (2)*	7.4677***	*(3) = (4)*	8.3363***
P-value		0.0063		0.0039
Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
Lender Controls	Yes	Yes	Yes	Yes
Observations	37,273	5,317	37,273	5,317
Adjusted R-squared	0.342	0.405	0.343	0.404

Table 10. Mechanism: Forest loss and firm operation

This table presents a firm-level analysis of how large forest loss events affect firm-level cash flow differently based on the firm's forest dependency. The dependent variable is *Cash flow*, calculated by dividing operating cash flow by the previous year tangible assets. *Top dependency* is a dummy variable equals one if the firm's forest-dependency score is above top 30% of the sample, and zero if below bottom 30%. Columns (1) and (2) use *Post large fire loss* as the large forest loss time indicator, which is defined as one if two years after a large fire loss event, and zero before an event. Columns (3) and (4) use *Post large anthropogenic loss* as the large forest loss time indicator, which is defined as one if two years after a large human-induced event, and zero before an event. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Cash flow				
Post large loss measure	*Fire loss*		*Anthropogenic loss*	
	(1)	(2)	(3)	(4)
Top dependency	-0.0344	-0.0288	-0.257**	-0.307*
	(0.110)	(0.0848)	(0.107)	(0.153)
Post large loss	0.138		0.0361	
	(0.0868)		(0.0783)	
Top dependency×*Post large loss*	-0.245*		0.0497	
	(0.120)		(0.133)	
Post large loss (t-2)		0.0938*		-0.0545
		(0.0486)		(0.181)
Post large loss (t-1)		0.0544		0.0108
		(0.0525)		(0.0784)
Post large loss (t+1)		0.207**		-0.0152
		(0.0833)		(0.142)
Post large loss (t+2)		0.170		0.00433
		(0.113)		(0.167)
Top dependency×*Post large loss (t-2)*		0.00593		0.0362
		(0.155)		(0.243)
Top dependency×*Post large loss (t-1)*		-0.0268		0.0492
		(0.105)		(0.123)
Top dependency×*Post large loss (t+1)*		-0.293***		-0.0169
		(0.0994)		(0.144)
Top dependency×*Post large loss (t+2)*		-0.221*		0.206
		(0.120)		(0.209)
Firm size	-0.0363***	-0.0340**	-0.0465*	-0.0538**
	(0.0115)	(0.0137)	(0.0264)	(0.0242)
Leverage	-0.0754	-0.111	-0.0588	-0.232
	(0.147)	(0.155)	(0.180)	(0.214)
ROA	1.829***	1.981***	1.799***	1.839***
	(0.519)	(0.548)	(0.490)	(0.492)
Liquidity	0.464	0.588	0.0288	-0.244
	(0.380)	(0.371)	(0.601)	(0.500)
Log credit rating	-0.00506	-0.0114	-0.0263	-0.0259
	(0.0208)	(0.0203)	(0.0179)	(0.0166)
Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,928	3,649	1,581	1,988
Adjusted R-squared	0.0736	0.0742	0.0772	0.0773

Table 11. Ex-post outcome in production

This table reports the firm-level results examining the effect of receiving loans after forest loss on the firm's supply chain. In both Panel A and Panel B, the dependent variable for columns (1) and (2) is *Supply dependency*, measuring the proportion of inputs that comes from forest-dependent suppliers for each firm, calculated as the sum of sales-weighted supplier's *Dependency* for a firm. The dependent variable for columns (3) and (4) is *Country-adj supply*, measuring the proportion of inputs that comes from forest-dependent suppliers of high-deforestation-risk countries for each firm, calculated as the sum of sales-weighted supplier's *Weighted dependency* for a firm. *If get loan* is defined as one if the firm gets syndicate loan in the same year or within one year following the forest loss. Panel A uses *Post large anthropogenic loss* as the time indicator, which equals one if three years after a large human-induced forest loss, and zero if three years before. Panel B uses *Post large fire loss* as the time indicator, which equals one if three years after a large fire-induced forest loss, and zero if three years before. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Transition in supply chain after large human-induced loss

Dependent variable	*Supply dependency*		*Country-adj supply*	
Outcome window (forward)	*+3 years*	*+4 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	0.0593**	0.0634**	0.111**	0.115**
	(0.0273)	(0.0295)	(0.0417)	(0.0440)
Post large anthropogenic loss	0.0423*	0.0396	0.0613	0.0577
	(0.0235)	(0.0243)	(0.0387)	(0.0402)
If get loan×*Post large anthropogenic loss*	-0.0426*	-0.0437	-0.0703**	-0.0711**
	(0.0225)	(0.0277)	(0.0250)	(0.0321)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	523	523	523	523
Adjusted R-squared	0.330	0.345	0.349	0.365

Panel B. Transition in supply chain after large forest loss from fire

Dependent variable	*Supply dependency*		*Country-adj supply*	
Outcome window (forward)	*+3 years*	*+4 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	0.0559**	0.0549**	0.0802*	0.0769*
	(0.0254)	(0.0258)	(0.0440)	(0.0432)
Post large fire loss	-0.00661	-0.00748	-0.0197	-0.0210
	(0.0201)	(0.0195)	(0.0395)	(0.0378)
If get loan×*Post large fire loss*	-0.0262	-0.0244	-0.0369	-0.0334
	(0.0215)	(0.0222)	(0.0384)	(0.0381)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	615	615	615	615
Adjusted R-squared	0.156	0.165	0.168	0.177

Table 12. Ex-post outcome in reforestation

This table reports the firm-level results examining the effect of receiving loans after human-induced loss on the reforestation around a firm. In both Panel A and Panel B, the dependent variable is *NDVI*, measuring the greenness of vegetation of the land surface around a firm on a scale from 0 to 100. The time indicator is *Post large anthropogenic loss*, which equals one if three years after a large human-induced forest loss, and zero if three years before. *If get loan* is defined as one if the firm gets syndicate loan in the same year or within one year following the forest loss. Panel A report the tests using full sample, and Panel B report the subsample of firms with forest dependency score above median. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Outcome in reforestation: Full sample

Dependent variable: NDVI				
Outcome window (forward)	*+1 year*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	-0.224	-0.184	-0.150	-0.0940
	(0.710)	(0.701)	(0.697)	(0.696)
Post large anthropogenic loss	-2.271*	-2.059	-1.918	-1.781
	(1.314)	(1.360)	(1.395)	(1.393)
If get loan×*Post large anthropogenic loss*	1.174***	1.215***	1.200***	1.126***
	(0.334)	(0.359)	(0.359)	(0.359)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,322	4,322	4,322	4,322
Adjusted R-squared	0.178	0.176	0.170	0.163

Panel B. Outcome in reforestation: High forest dependency subsample

Dependent variable: NDVI				
Outcome window (forward)	*+1 year*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	0.727	0.796	0.858	0.928
	(1.053)	(1.045)	(1.044)	(1.053)
Post large anthropogenic loss	-2.230	-1.944	-1.869	-1.745
	(1.662)	(1.690)	(1.708)	(1.684)
If get loan×*Post large anthropogenic loss*	1.555**	1.575**	1.595**	1.525**
	(0.593)	(0.620)	(0.632)	(0.646)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,303	2,303	2,303	2,303
Adjusted R-squared	0.193	0.189	0.183	0.177

Table 13. Ex-post outcome in divesting pollutive plants

This table reports the firm-level results examining the effect of receiving loans after human-induced loss on divesting pollutive plants. The dependent variable is *Divestiture*, an indicator that equals 100 if the firm divests a forest-dependent pollutive plant in the following estimation window. *Anthropogenic loss* refers to firm-level forest loss from human activities in the previous year. *If get loan* is an indicator defined as one if the firm gets syndicate loan in a year, and zero otherwise. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Divestiture						
Type of divested plants	*Nonzero forest dependency*			*High forest dependency*		
Outcome window (forward)	*+2 years*	*+3 years*	*+4 years*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)	(5)	(6)
Dependency	-0.403	-0.726	-0.966	-0.403	-0.720	-0.958
	(0.291)	(0.450)	(0.609)	(0.289)	(0.447)	(0.605)
Anthropogenic loss	-0.0493	-0.154	-0.322	0.00416	-0.104	-0.269
	(0.121)	(0.146)	(0.187)	(0.113)	(0.132)	(0.170)
If get loan	0.575	0.868**	0.819	0.675*	0.890**	0.857
	(0.360)	(0.391)	(0.493)	(0.350)	(0.403)	(0.502)
Dependency×Anthropogenic loss	0.623	1.123*	1.526*	0.621	1.118*	1.520*
	(0.371)	(0.569)	(0.753)	(0.367)	(0.564)	(0.748)
Dependency× *If get loan*	-0.992**	-1.032**	-1.273**	-0.991**	-1.064**	-1.294**
	(0.423)	(0.454)	(0.520)	(0.412)	(0.441)	(0.507)
Anthropogenic loss× *If get loan*	-0.413*	-0.531**	-0.477**	-0.461**	-0.563**	-0.513**
	(0.201)	(0.192)	(0.218)	(0.203)	(0.204)	(0.228)
Dependency×Anthropogenic loss	1.095***	1.118***	1.215***	1.090***	1.123***	1.210***
× *If get loan*	(0.282)	(0.304)	(0.390)	(0.279)	(0.299)	(0.384)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,313	7,313	7,313	7,313	7,313	7,313
Adjusted R-squared	0.0129	0.0198	0.0233	0.0152	0.0223	0.0255

Appendix

Table A.1. Variable definition

Variable	Definition	Source
Acute physical risk	The frequency of mentions of the unigrams or bigrams related to the acute climate discussion in the proximity of risk synonyms in the previous year earnings call transcript, divided by the total length of the transcript and standardized.	Li et al. (2024), StreetEvents
Anthropogenic loss	The size of forest loss from human activities within 10km around a firm's headquarter in the previous year in km².	Hansen et al. (2013), Tyukavina et al. (2022)
Bank size	The log value of total assets (million USD) of a bank in year t-1.	Compustat, Refinitiv, BankFocus
Book value of debt	The sum of long-term debt, notes payable, and the current portion of long-term debt.	Compustat, Refinitiv,
Cash flow	Operating cash flow divided by previous year tangible assets of a firm in year t-1.	Compustat, Refinitiv
Chronic physical risk	The frequency of mentions of the unigrams or bigrams related to the chronic climate discussion in the proximity of risk synonyms in the previous year earnings call transcript, divided by the total length of the transcript and standardized.	Li et al. (2024), StreetEvents
Country-adj supply	The proportion of inputs that comes from forest-dependent suppliers of high-deforestation-risk countries for each firm, calculated as the sum of sales-weighted supplier's *Weighted dependency* for a firm.	Compustat Segment
Dependency	Level of production processes' dependency on forest of a firm at the 2-digit SIC level on a 0-5 scale.	ENCORE
Divestiture	An indicator that equals 100 if the firm divests a forest-dependent pollutive plant in the following estimation window.	TRI EPA, SDC M&A
Fire loss	The area of forest loss from fire within 10km around a firm's headquarter in the previous year in km².	Tyukavina et al. (2022)
Firm commit	The total number of firm disclosures that mentioned "deforestation" in the previous year. Corporate filings include: ESG reports, annual reports; SEC filings, etc.	Refinitiv AdvFil
Firm size	The log value of total assets (million USD) of a firm in year t-1.	Compustat, Refinitiv
High dependency	An indicator that equals one if the firm's dependent score *Dependency* is above the sample median, and zero otherwise.	ENCORE
If base prime	An indicator that equals one if the base rate for a loan is the prime rate rather than LIBOR, and zero otherwise.	DealScan
If fire	An indicator that equals one if a firm has non-zero fire-induced loss in the previous year, and zero otherwise.	Tyukavina et al. (2022)
If get loan	An indicator that equals one if the firm gets syndicate loan in the same year or within one year following the forest loss, and zero otherwise.	DealScan, Hansen et al. (2013), Tyukavina et al. (2022)
If refinance	An indicator that equals one if the loan refinances a previous loan, and zero otherwise.	DealScan
If secured loan	An indicator that equals one if the loan tranche (facility) is secured, and zero otherwise.	DealScan
Leverage	Total liabilities divided by total assets of a firm in year t-1.	Compustat, Refinitiv
Liquidity	Cash divided by total assets of a firm in year t-1.	Compustat, Refinitiv
Loan purpose	An indicator that equals one if the loan tranche (facility) purpose is M&A, and zero otherwise.	DealScan
Log amount	The log value of loan amount (million USD).	DealScan
Log credit rating	Moody's short-term issuer rating of a firm in year t-1.	Refinitiv
Log maturity	The log value of loan maturity (month).	DealScan

NDVI	MODIS normalized difference vegetation index (NDVI) within 10km around the firm's headquarter, measuring how "green" a vegetation area is from -1 to 1. The measure is normalized to 0-100 scale in the regressions.	MODIS NDVI
Post large anthropogenic loss	A time indicator that equals one if the period within estimation window is after a large human-induced forest loss, and zero if before.	Hansen et al. (2013), Tyukavina et al. (2022)
Post large fire loss	A time indicator that equals one if the period within estimation window is after a large fire-induced forest loss, and zero if before.	Tyukavina et al. (2022)
Post EUDR	A time indicator defined as one after the first deforestation framework stage (July 2019), and zero otherwise.	European Commission
Post EUDR (phase 1)	A time indicator defined as one for the period between the first deforestation policy framework and the regulation's entry into force (June 2023), and zero otherwise.	European Commission
Post EUDR (phase 2)	A time indicator defined as one for the period after the EUDR goes into force (June 2023), and zero otherwise.	European Commission
Reforest	An indicator that equals 100 if the firm claims to engage in reforestation activities in their disclosures in the following estimation window.	Refinitiv AdvFil
Repeated lending	An indicator that equals 1 if there is a past relationship with any of the lead banks in the last five years before the present loan and 0 otherwise.	DealScan
ROA	Net profit divided by total assets in year t-1.	Refinitiv, Compustat
Supply dependency	The proportion of inputs that comes from forest-dependent suppliers for each firm, calculated as the sum of sales-weighted supplier's *Dependency* for a firm.	Compustat Segment
Top dependency	An indicator that equals one if the firm's dependent score *Dependency* is above the top 30% of the sample, and zero if below bottom 30%.	ENCORE
Transition risk	The frequency of mentions of the unigrams or bigrams related to the transition climate discussion in the proximity of risk synonyms in the previous year earnings call transcript, divided by the total length of the transcript and standardized.	Li et al. (2024), StreetEvents
Weighted dependency	Country-year-level forest loss-weighted dependency score in year t-1, rescaled to a range of 0 to 5. The measure is calculated as $\text{Dependency} \times (1 + \text{forest loss}_{c,t})$, where $\text{forest loss}_{c,t}$ is the country-year total area of forest loss. Both *Dependency* and $\text{forest loss}_{c,t}$ are normalized to 0-1 during the calculation.	ENCORE, GLAD
Yield spread	All-in-spread drawn (AISD) divided by 100.	DealScan

Online Appendix

Table B.1. Forest loss and loan spreads controlling for climate risk index

This table reports the robustness results controlling the climate risk index of Li et al. (2024) for the tests examining how forest loss impacts yield spreads differently for firms based on their forest dependency. The regression sample is the US listed firms with call transcripts in a year. The dependent variable is *Yield spread*, measured by AISD divided by 100. Columns (1) and (2) use *Dependency* to measure forest dependency at the 2-digit SIC level, and columns (3) to (4) use *Weighted dependency*, which adjusts for risks associated with country-year-level forest loss and is rescaled to a range of 0 to 5. *Fire loss* refers to firm-level forest loss from fire in the previous year, and *Anthropogenic loss* refers to firm-level forest loss from human activities in the previous year. *Acute physical risk*, *Chronic physical ri*sk, and *Transition risk* are three climate risk proxies calculated by the frequency of mentions of the unigrams or bigrams related to the acute, chronic, and transition climate discussion, respectively, in the previous year earnings call transcript, divided by the total length of the transcript and standardized (Li et al. 2024). Definitions for all variables are provided in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC level and year level, with values reported in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Yield spread				
Dependency measures	*Dependency*		*Weighted dependency*	
	(1)	(2)	(3)	(4)
Dependency measure	0.0109	0.0146	-0.000578	0.00345
	(0.0657)	(0.0672)	(0.0719)	(0.0737)
Fire loss	-0.223	-0.241	-0.275	-0.294
	(0.270)	(0.272)	(0.281)	(0.284)
Anthropogenic loss	0.131	0.130*	0.115	0.115
	(0.0783)	(0.0748)	(0.0824)	(0.0786)
Dependency measure × *Fire loss*	0.587***	0.584***	0.781***	0.776***
	(0.123)	(0.125)	(0.166)	(0.166)
Dependency measure × *Anthropogenic loss*	-0.0862	-0.0873	-0.0727	-0.0747
	(0.0652)	(0.0642)	(0.0723)	(0.0708)
Acute physical risk		0.0225		0.0228
		(0.0586)		(0.0593)
Chronic physical risk		0.00593		0.00603
		(0.0365)		(0.0366)
Transition risk		-0.0712***		-0.0709***
		(0.0199)		(0.0197)
Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
Lender Controls	Yes	Yes	Yes	Yes
Observations	4,277	4,277	4,277	4,277
Adjusted R-squared	0.368	0.369	0.368	0.369

Table B.2. Country heterogeneity of EUDR's effect on yield spreads

This table presents the robustness results on how the EUDR introduction affects yield spreads for forest-dependent firms compared to other firms when human-induced loss occurred. The analysis examines how EU banks and non-EU banks respond differently to EU operators. The dependent variable is *Yield spread*. Columns (1) and (2) use *Dependency* to measure forest dependency, and columns (3) and (4) use *Weighted dependency* to account for country-year-level forest loss risk. *Post EUDR* is a time indicator, defined as one after the deforestation framework stage (July 2019), and zero otherwise. Columns (1) and (3) examine EU banks with EU operators, and Columns (2) and (4) examine non-EU banks with EU operators. Loan controls include *If secured loan, If base prime, If refinance, Repeated lending, Loan purpose, Log loan amount, and Log maturity*. Borrower controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. Lender controls include *Bank size*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Yield spread				
Dependency measure	*Dependency*		*Weighted dependency*	
Bank country	*EU bank*	*Non-EU*	*EU bank*	*Non-EU*
	(1)	(2)	(3)	(4)
Dependency measure	-0.126*	-0.135	-0.149	-0.144
	(0.0723)	(0.122)	(0.149)	(0.200)
Anthropogenic loss	0.0696	-0.0716	0.0833	-0.111
	(0.187)	(0.220)	(0.191)	(0.244)
Post EUDR	0.339**	-0.952**	0.365*	-0.891**
	(0.161)	(0.359)	(0.181)	(0.378)
Dependency measure×Anthropogenic loss	0.0412	0.0624	0.0426	0.158
	(0.176)	(0.236)	(0.298)	(0.415)
Dependency measure×*Post EUDR*	0.0662	0.671*	0.0723	0.994
	(0.122)	(0.359)	(0.280)	(0.616)
Anthropogenic loss×*Post EUDR*	-1.792**	0.533	-1.564	0.714
	(0.767)	(1.421)	(0.955)	(1.418)
Dependency measure×Anthropogenic loss×*Post EUDR*	1.686**	-0.423	2.568*	-1.016
	(0.643)	(1.698)	(1.382)	(2.796)
Chi-square test	*(1) = (2)*	3.0201*	*(3) = (4)*	2.7673*
P-value		0.0822		0.0962
Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
Lender Controls	Yes	Yes	Yes	Yes
Observations	6,171	5,671	6,171	5,671
Adjusted R-squared	0.471	0.441	0.469	0.440

Table B.3. Ex-post outcome in reforestation after fire-induced loss

This table reports the firm-level results examining the effect of receiving loans after fire-induced loss on the reforestation around a firm. In both Panel A and Panel B, the dependent variable is *NDVI*, measuring the greenness of vegetation of the land surface around a firm on a scale from 0 to 100. The time indicator is *Post large fire loss*, which equals one if three years after a large fire-induced forest loss, and zero if three years before. *If get loan* is defined as one if the firm gets syndicate loan in the same year or within one year following the forest loss. Panel A report the tests using full sample, and Panel B report the subsample of firms with forest dependency score above median. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Outcome in reforestation: Full sample

Dependent variable: NDVI				
Outcome window (forward)	*+1 year*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	-0.0657	-0.112	-0.145	-0.177
	(0.839)	(0.840)	(0.837)	(0.835)
Post large fire loss	0.0504	0.535	0.836	0.870
	(2.412)	(2.471)	(2.508)	(2.512)
If get loan×*Post large fire loss*	-0.160	-0.0949	-0.0556	-0.0334
	(0.539)	(0.531)	(0.539)	(0.556)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,811	6,811	6,811	6,811
Adjusted R-squared	0.0722	0.0720	0.0717	0.0714

Panel B. Outcome in reforestation: High forest dependency subsample

Dependent variable: NDVI				
Outcome window (forward)	*+1 year*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	0.719	0.662	0.632	0.613
	(0.966)	(0.972)	(0.968)	(0.966)
Post large fire loss	-0.908	-0.495	-0.226	-0.204
	(2.394)	(2.447)	(2.468)	(2.478)
If get loan×*Post large fire loss*	-0.346	-0.277	-0.247	-0.247
	(0.573)	(0.547)	(0.552)	(0.574)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,648	3,648	3,648	3,648
Adjusted R-squared	0.0928	0.0929	0.0926	0.0921

Table B.4. Loan receipt and differences in firms' book value of debt

This table compares the book value of debt between firms that receive bank syndicate loans in a year (*If get loan* = 1) and those that do not (*If get loan* = 0). The book value of debt is measured as the sum of long-term debt, notes payable, and the current portion of long-term debt.

	If get loan=1		If get loan=0		Diff: Yes - No
	Mean (std. dev.)	Obs	Mean (std. dev.)	Obs	Mean (std. err.)
Book value of debt (m$)	33,126.102 (94,882.800)	23,891	28,191.304 (86,935.547)	93,292	4,934.7978*** (642.5301)

Table B.5. Selection into granting loans

This table reports the first-stage probit model estimating the likelihood of a firm receiving a syndicated loan in a given year. The dependent variable *If get loan* is an indicator equal to one if the firm obtains a syndicated loan and zero otherwise. Firm-level controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. Columns (2) and (3) include *Anthropogenic loss* and *Dependency*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: If get loan			
	(1)	(2)	(3)
Firm size	0.00830**	0.00748*	0.00740*
	(0.00401)	(0.00390)	(0.00394)
Leverage	0.150***	0.155***	0.158***
	(0.0383)	(0.0404)	(0.0386)
ROA	0.299***	0.324***	0.326***
	(0.0465)	(0.0463)	(0.0473)
Liquidity	-0.715***	-0.725***	-0.720***
	(0.0604)	(0.0577)	(0.0542)
Log credit rating	0.0339***	0.0309***	0.0308***
	(0.00726)	(0.00755)	(0.00756)
Anthropogenic loss		0.00748*	0.0133
		(0.00390)	(0.0155)
Dependency			0.0110
			(0.0117)
Constant	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	104,166	99,198	99,198
Adjusted R-squared	0.00656	0.00643	0.00647

Table B.6. Robustness: Ex-post outcome in production

This table reports the robustness results examining the effect of receiving loans after forest loss on the firm's supply chain, controlling for selection bias using the Inverse Mills Ratio (IMR) from the first-stage probit model (Table B.5). In both Panel A and Panel B, the dependent variable in columns (1) and (2) is *Supply dependency*, measuring the proportion of inputs sourced from forest-dependent suppliers. Columns (3) and (4) use *Country-adj supply*, capturing inputs from forest-dependent suppliers in high-deforestation-risk countries. *If get loan* equals one if the firm secures a syndicated loan in the same year or within one year after forest loss. Panel A defines the post-event period based on large human-induced forest loss, while Panel B uses large fire-induced forest loss. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, *Log credit rating*, and the IMR term. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Transition in supply chain after large human-induced loss

Dependent variable	*Supply dependency*		*Country-adj supply*	
Outcome window (forward)	*+3 years*	*+4 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	0.0592**	0.0635**	0.112**	0.115**
	(0.0272)	(0.0293)	(0.0412)	(0.0436)
Post large anthropogenic loss	0.0293	0.0277	0.0471	0.0446
	(0.0247)	(0.0253)	(0.0409)	(0.0428)
If get loan×*Post large anthropogenic loss*	-0.0448**	-0.0459	-0.0736***	-0.0744**
	(0.0215)	(0.0267)	(0.0243)	(0.0311)
IMR (*If get loan*)	-3.643**	-3.358**	-4.083*	-3.785*
	(1.466)	(1.281)	(2.235)	(2.116)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	518	518	518	518
Adjusted R-squared	0.342	0.355	0.355	0.370

Panel B. Transition in supply chain after large forest loss from fire

Dependent variable	*Supply dependency*		*Country-adj supply*	
Outcome window (forward)	*+3 years*	*+4 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	0.0549**	0.0539**	0.0789*	0.0758*
	(0.0248)	(0.0254)	(0.0435)	(0.0430)
Post large fire loss	-0.00660	-0.00747	-0.0197	-0.0209
	(0.0198)	(0.0193)	(0.0392)	(0.0376)
If get loan×*Post large fire loss*	-0.0254	-0.0237	-0.0360	-0.0326
	(0.0219)	(0.0229)	(0.0394)	(0.0396)
IMR (*If get loan*)	2.582	2.464	3.070	3.001
	(4.255)	(4.175)	(6.584)	(6.476)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	614	614	614	614
Adjusted R-squared	0.158	0.167	0.168	0.177

Table B.7. Robustness: Ex-post outcome in reforestation

This table reports the robustness results examining the effect of receiving loans after human-induced forest loss on reforestation, controlling for selection bias using the Inverse Mills Ratio (IMR) from the first-stage probit model (Table B.5). In both Panel A and Panel B, the dependent variable is *NDVI*, which measures the greenness of vegetation around a firm on a scale from 0 to 100. *If get loan* equals one if the firm obtains a syndicated loan in the same year or within one year after forest loss. The time indicator is *Post large anthropogenic loss*, which equals one if three years after a large human-induced forest loss, and zero if three years before. Panel A report the tests using full sample, and Panel B report the subsample of firms with forest dependency score above median. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, *Log credit rating*, and the IMR term. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Outcome in reforestation: Full sample

Dependent variable: NDVI				
Outcome window (forward)	*+1 year*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	-0.103	-0.0796	-0.0446	0.00227
	(0.696)	(0.690)	(0.687)	(0.688)
Post large anthropogenic loss	-2.901**	-2.692*	-2.584*	-2.454*
	(1.297)	(1.340)	(1.370)	(1.370)
If get loan×*Post large anthropogenic loss*	1.005**	1.063**	1.045**	0.979**
	(0.385)	(0.404)	(0.403)	(0.390)
IMR (*If get loan*)	-282.2***	-281.0***	-295.1***	-297.0***
	(82.76)	(80.66)	(82.31)	(83.92)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,288	4,288	4,288	4,288
Adjusted R-squared	0.191	0.189	0.183	0.177

Panel B. Outcome in reforestation: High forest dependency subsample

Dependent variable: NDVI				
Outcome window (forward)	*+1 year*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
If get loan (t or t+1)	0.583	0.638	0.703	0.774
	(1.158)	(1.147)	(1.144)	(1.152)
Post large anthropogenic loss	-1.851	-1.558	-1.482	-1.355
	(1.749)	(1.774)	(1.788)	(1.756)
If get loan×*Post large anthropogenic loss*	1.666**	1.699**	1.715**	1.644**
	(0.627)	(0.654)	(0.667)	(0.684)
IMR (*If get loan*)	146.4	150.0	150.3	151.4
	(113.0)	(113.7)	(113.7)	(114.4)
Constant	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,286	2,286	2,286	2,286
Adjusted R-squared	0.201	0.199	0.193	0.188

Table B.8. Robustness: Ex-post outcome in divesting pollutive plants

This table reports the firm-level results examining the effect of receiving loans after human-induced forest loss on the divestiture of pollutive, forest-dependent plants, controlling for selection bias using the Inverse Mills Ratio (IMR) from the first-stage probit model (Table B.5). The dependent variable is *Divestiture*, an indicator that equals 100 if the firm divests a forest-dependent pollutive plant in the following estimation window. *Anthropogenic loss* refers to firm-level forest loss from human activities in the previous year. *If get loan* is an indicator defined as one if the firm gets syndicate loan in a year, and zero otherwise. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, *Log credit rating*, and the IMR term. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Divestiture						
Type of divested plants	*Nonzero forest dependency*			*High forest dependency*		
Outcome window (forward)	*+2 years*	*+3 years*	*+4 years*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)	(5)	(6)
Dependency	-1.172	-2.043*	-2.789*	-1.179	-1.999*	-2.648*
	(0.731)	(1.078)	(1.436)	(0.748)	(1.103)	(1.480)
Anthropogenic loss	-0.681	-1.235	-1.819	-0.633	-1.155	-1.657
	(0.592)	(0.864)	(1.127)	(0.598)	(0.864)	(1.146)
If get loan	0.577	0.871**	0.824	0.677*	0.894**	0.862
	(0.354)	(0.393)	(0.493)	(0.346)	(0.410)	(0.501)
Dependency×Anthropogenic loss	0.615	1.109*	1.507*	0.613	1.105*	1.503*
	(0.373)	(0.574)	(0.761)	(0.369)	(0.569)	(0.755)
Dependency× *If get loan*	-0.998**	-1.044**	-1.289**	-0.998**	-1.075**	-1.308**
	(0.416)	(0.447)	(0.512)	(0.405)	(0.435)	(0.499)
Anthropogenic loss× *If get loan*	-0.412*	-0.529**	-0.474**	-0.460**	-0.561**	-0.510**
	(0.200)	(0.195)	(0.222)	(0.202)	(0.208)	(0.231)
Dependency×Anthropogenic loss	1.104***	1.133***	1.235***	1.099***	1.137***	1.229***
× *If get loan*	(0.288)	(0.308)	(0.394)	(0.284)	(0.305)	(0.387)
IMR (*If get loan*)	-75.08	-128.5	-177.8	-75.71	-124.8	-164.9
	(62.50)	(95.06)	(122.4)	(64.71)	(96.52)	(124.9)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,313	7,313	7,313	7,313	7,313	7,313
Adjusted R-squared	0.0130	0.0202	0.0240	0.0153	0.0227	0.0261

Table B.9. Reforestation: Alternative measure using firm disclosures

This table reports the robustness results on the effect of receiving loans after human-induced loss on firms' reforestation engagement. The dependent variable is *Reforest*, an indicator that equals 100 if the firm claims to engage in reforestation activities in their disclosures in the following estimation window. *Anthropogenic loss* refers to firm-level forest loss from human activities in the previous year. *If get loan* is an indicator defined as one if the firm gets syndicate loan in a year, and zero otherwise. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, and *Log credit rating*. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Reforest				
Outcome window (forward)	*+1 years*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
Dependency	0.268	0.184	0.0437	-0.0712
	(0.297)	(0.334)	(0.353)	(0.402)
Anthropogenic loss	0.893***	1.138***	1.228**	1.286**
	(0.293)	(0.378)	(0.436)	(0.471)
If get loan	1.024***	1.253***	1.492***	1.548***
	(0.301)	(0.335)	(0.336)	(0.359)
Dependency×Anthropogenic loss	-0.499**	-0.536**	-0.421*	-0.310
	(0.187)	(0.209)	(0.234)	(0.287)
Dependency× *If get loan*	-0.840***	-0.881**	-1.003***	-1.042**
	(0.269)	(0.361)	(0.337)	(0.403)
Anthropogenic loss× *If get loan*	0.0102	0.0488	0.0395	0.0946
	(0.117)	(0.197)	(0.161)	(0.228)
Dependency×Anthropogenic loss× *If get loan*	0.657***	0.756***	0.705***	0.560***
	(0.127)	(0.153)	(0.123)	(0.180)
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	95,595	95,595	95,595	95,595
Adjusted R-squared	0.0335	0.0389	0.0408	0.0415

Table B.10. Robustness: Selection-adjusted results for alternative reforestation measure

This table reports the robustness results examining the effect of receiving loans after human-induced forest loss on firms' reforestation engagement, controlling for selection bias using the Inverse Mills Ratio (IMR) from the first-stage probit model (Table B.5). The dependent variable is *Reforest*, an indicator that equals 100 if the firm claims to engage in reforestation activities in their disclosures in the following estimation window. *Anthropogenic loss* refers to firm-level forest loss from human activities in the previous year. *If get loan* is an indicator defined as one if the firm gets syndicate loan in a year, and zero otherwise. Firm controls include *Firm size*, *Leverage*, *ROA*, *Liquidity*, *Log credit rating*, and the IMR term. All variables are defined in Appendix Table A.1. Standard errors are clustered at the 2-digit SIC and year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable: Reforest				
Outcome window (forward)	*+1 years*	*+2 years*	*+3 years*	*+4 years*
	(1)	(2)	(3)	(4)
Dependency	3.094***	3.678***	3.839***	3.969***
	(0.780)	(0.950)	(1.056)	(1.141)
Anthropogenic loss	3.219***	4.012***	4.350***	4.609***
	(0.776)	(0.911)	(1.002)	(1.060)
If get loan	1.021***	1.249***	1.487***	1.543***
	(0.303)	(0.339)	(0.342)	(0.366)
Dependency×Anthropogenic loss	-0.503**	-0.541**	-0.426*	-0.316
	(0.184)	(0.205)	(0.228)	(0.279)
Dependency× *If get loan*	-0.870***	-0.917**	-1.043***	-1.084**
	(0.272)	(0.369)	(0.347)	(0.412)
Anthropogenic loss× *If get loan*	-0.00173	0.0341	0.0234	0.0775
	(0.120)	(0.194)	(0.162)	(0.227)
Dependency×Anthropogenic loss× *If get loan*	0.654***	0.753***	0.701***	0.556***
	(0.126)	(0.151)	(0.138)	(0.187)
IMR (*If get loan*)	272.7***	337.1***	366.2***	389.8***
	(76.50)	(91.59)	(100.3)	(105.9)
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	95,595	95,595	95,595	95,595
Adjusted R-squared	0.0347	0.0403	0.0422	0.0429

References

Li Q, Shan H, Tang Y, Yao V (2024) Corporate climate risk: Measurements and responses. *The Review of Financial Studies* 37(6):1778–1830.