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Essays in Accounting and Finance

Thesis

WIRTSCHAFTSUNIVERSITÄT WIEN
Vienna University of Economics and Business

PhD Dissertation

Title of the academic paper(s):	Essays in Accounting and Finance: 1) Disclosure Regulation, Corruption, and Investment: Evidence from Natural Resource Extraction 2) Procyclicality of U.S. Bank Leverage 3) Fishing with Pearls: The Value of Lending Relationships with Prestigious Firms
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Essays in Accounting and Finance

Thomas Rauter

Abstract

This dissertation studies real effects of disclosure regulation and topics at the intersection of accounting and banking. It consists of three papers.

The notion that mandating disclosure stimulates desirable and discourages undesirable behavior by the disclosing party is an important motivation for financial reporting and transparency regulation. However, there is relatively little evidence on the real effects of mandatory disclosure that directly speaks to this motivation. In **"Disclosure Regulation, Corruption, and Investment: Evidence from Natural Resource Extraction"**, I investigate the real effects of mandatory extraction payment disclosures, which require European oil, gas, and mining firms to publicly disclose their payments to foreign host governments in a granular report on their corporate website. Extraction payment disclosures are substantially more disaggregated compared to previous payment records, allowing activist groups to identify payment discrepancies and exert societal pressure on extractive firms. I exploit plausibly-exogenous variation in the adoption of extraction payment reports across European countries and firms' fiscal-year ends to disentangle the disclosure effects from concurrent but unrelated macroeconomic and regulatory changes. Using manually-collected host country data on firms' extractive activities abroad, I document that disclosing companies increase their payments to foreign host governments but decrease investments relative to tightly-matched, non-disclosing competitors from around the world. The effects are particularly strong for large firms and for firms that sell their products directly to end consumers. Moreover, I find that extraction payment reports are associated with investment reallocations within disclosing firms and across disclosing and non-disclosing companies. I contribute to the prior literature by showing that social responsibility disclosures can have sizeable real effects at the micro level, especially if the threat of public shaming by specialized activist groups disciplines companies not to engage in illicit practices. However, I do not find that extraction payment disclosures are associated with improved measures of corruption at the aggregate host country level, which

questions recent unilateral efforts by Western countries to address foreign policy objectives by imposing disclosure regulation on only a subset of companies in the global marketplace.

The financial crisis of 2007-2009 triggered a vigorous debate about the role of fair value accounting and revived discussions about procyclicality in banking. While there is evidence that fair value accounting did not play a major role during the crisis, there is still the concern that fair value accounting contributes to instability by inflating credit bubbles via procyclical leverage. In **"Procyclicality of U.S. Bank Leverage"** *(Journal of Accounting Research (2017))*, Christian Laux and I investigate the determinants of procyclical book leverage for U.S. commercial and savings banks in light of the current debate about the link between accounting and financial stability. Our evidence is not consistent with the notion that fair value accounting contributes to procyclical leverage or that historical cost accounting reduces procyclicality. Overall, we conclude that the business model of banks is more important for procyclical leverage than accounting or bank regulation.

A large literature examines the economic benefits of private information production by banks within lending relationships. However, lending relationships are also valuable to banks outside of specific firm-creditor ties. In practice, lenders frequently advertise their participation in syndicated loan transactions through "tombstone announcements" in financial magazines to raise their public profile and use existing lending relationships as a marketing tool to attract new borrowers. Despite anecdotal evidence that banks value the public recognition from high profile transactions, there is little evidence on how lending relationships with prestigious firms shape debt contracting. In **"Fishing with Pearls: The Value of Lending Relationships with Prestigious Firms"**, Alexander Mürmann, Christoph Scheuch, and I provide novel evidence of banks establishing lending relationships with prestigious firms to signal their quality and attract future business. Using unique survey data on firm-level prestige, we show that lenders compete more intensely for prestigious borrowers and offer lower upfront fees to initiate lending relationships with prestigious firms. We also find that banks expand their lending after winning prestigious clients. Prestigious firms benefit from these relationships as they face lower costs of borrowing even though prestige has no predictive power for credit risk. Our results are robust to matched sample analyses and a regression discontinuity design.

Disclosure Regulation, Corruption, and Investment: Evidence from Natural Resource Extraction*

Thomas Rauter†

May 2018

Abstract

I investigate the real effects of mandatory extraction payment disclosures, which require European oil, gas, and mining firms to publicly disclose their payments to foreign host governments in a granular report on their corporate website. Extraction payment disclosures are substantially more detailed compared to previous payment records, allowing activist groups to identify payment discrepancies and exert societal pressure on extractive firms. Using manually-collected host country data on firms' extractive activities abroad and exploiting the staggered, plausibly-exogenous adoption of extraction payment reports across European countries and firms' fiscal year ends, I document that disclosing companies increase their payments to host governments but decrease and reallocate investments relative to tightly-matched, non-disclosing competitors from around the world. The effects are particularly strong for large firms and for firms that sell their products directly to end consumers. My results suggest that social responsibility disclosures can have sizeable real effects, especially if public shaming by specialized activist groups disciplines companies not to engage in illicit practices. In contrast, extraction payment disclosures are not associated with improved measures of corruption at the aggregate host country level, which questions unilateral disclosure mandates aimed at addressing foreign policy objectives.

JEL-Classification: G14; G38; K22; L71; M41; M48; O10

Keywords: Real Effects; Disclosure Regulation; Corruption; Public Shaming; Corporate Social Responsibility

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*I am grateful to my PhD advisors Hans Christensen, João Granja, Christian Laux (chair), and Alexander Mürmann for their generous and invaluable guidance. I thank Milena Amann-Rauter, Ray Ball, John Barrios, Phil Berger, Matthias Breuer, John Gallemore, Luzi Hail, Tarek Hassan, Katharina Hombach, Christian Leuz, Lisa Yao Liu, Mark Maffett, Maximilian Muhn, Valeri Nikolaev, Christoph Scheuch, Rimmy Tomy, Josef Zechner as well as workshop participants at Bocconi University, Carnegie Mellon University (Tepper), Dartmouth (Tuck), Frankfurt School of Finance and Management, Harvard Business School, IESE, INSEAD, LMU Munich, the University of Chicago (Booth), the University of Mannheim, Stanford University, the University of Pennsylvania (Wharton), and WU Vienna for helpful comments and suggestions. I also thank Dominic Eagleton (Global Witness), Oliver Masetti (World Bank) and Daniel Turnheim (OMV) for providing institutional information and many practical insights. I am indebted to Hans Christensen, Christian Leuz, and Luzi Hail for sharing their data on EU implementation characteristics of the Market Abuse and Transparency Directives. Alexander and Hannah Amann provided excellent research assistance. Parts of this paper were completed while I was visiting the University of Chicago Booth School of Business.

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1 Introduction

Policymakers increasingly require firms to publicly disclose information about corporate social responsibility (CSR). An important motivation for CSR disclosures is to equip interested parties with information to exert societal pressure on companies and discourage illegitimate firm behavior (EY (2013); Fung et al. (2007)). Despite its regulatory motivation and popularity as a policy tool, we know little about the real effects of CSR disclosures and their underlying economic mechanisms (Leuz and Wysocki (2016)).[1]

In this paper, I examine the real effects of mandatory extraction payment disclosures, which require European oil, gas, and mining firms (henceforth, "extractive firms") to publicly disclose their payments to foreign host governments in a granular report on their corporate website ("PGD regulation").[2] The key difference between these disclosures and previously available payment records is that the information in extraction payment reports is substantially more detailed. Unlike before, firm-level payments are not only disaggregated by the receiving host country government, but also by extractive project and payment type. While the underlying payment information is generated by firms' financial reporting systems and reconciled with financial statements, extraction payment disclosures are published independently from the annual filings on a different date.

By nature of their business, extractive companies frequently venture abroad to extract oil, gas, or minerals in foreign host countries that are well endowed with natural resources. Firms compensate host countries for the resource extraction and official extraction agreements determine the payments that companies make to foreign governments.[3] Extractive payments are an essential source of government income for (poor) countries (Collier (2007)). However, policymakers and economists are concerned that host countries do not obtain a fair share of extractive sector revenues, thereby limiting the extent to which natural resource endowments stimulate economic development in these nations (Humphreys et al.

[1] I define real effects as situations in which the disclosing person or reporting entity changes its behavior in the real economy as a result of the disclosure mandate (Leuz and Wysocki (2016)).

[2] Throughout this paper, I use the terms "extraction payment disclosures" and "PGD regulation" interchangeably.

[3] Depending on the stage of the project lifecycle, extractive companies make different kinds of payments such as royalties, license fees, or signature bonuses. Open Oil (2012) and Resource Contracts (2014) summarize the different stages of the extractive project lifecycle. Global Witness (2017) provides a detailed description of each payment type including examples.

(2007); Acemoglu and Robinson (2012)). For one, host country officials frequently negotiate corrupt deals with extractive companies (Global Witness (2017)). The notion is that extractive firms bribe government bureaucrats to receive payment concessions in excess of the illicit kickback (Financial Times (2012); EY (2014)). Indeed, the OECD (2014) estimates that 19 percent of all foreign bribery cases occur in the oil, gas, and mining industries, which is higher than in any other sector.[4] For another, extractive companies employ aggressive payment avoidance strategies by underreporting extractive revenues or overreporting project costs.[5]

To fight corrupt business practices and improve extractive revenue collection, policymakers in Europe passed legislation that requires oil, gas, and mining companies to provide a yearly report containing detailed project-level information on firms' payments to foreign host countries (European Commission (2013)). The recent decision by the U.S. government to roll back PGD regulation for American oil, gas, and mining firms (CNN (2017)) triggered a vigorous policy debate about the benefits and costs of extraction payment disclosures. Proponents argue that the higher disaggregation of extractive payments in PGD reports allows a wide range of interested parties (e.g., NGOs, civil society) to better monitor extractive activities, identify payments that are "too low" (red flags), and exert public pressure by contacting journalists to encourage media coverage or lobbying anti-corruption agencies to investigate. Prior information, for example about project-specific extraction quantities and royalty rates, only allowed activist groups to determine the payments that firms are *expected to make* to foreign governments, but not how much companies *actually pay* to host countries.[6] This previously missing information is now publicly available in extraction payment disclosures. Once watchdogs expose extractive revenue losses, public

[4]There are many incidents where government bureaucrats sold licenses to extractive companies at below market prices in exchange for private benefits. Prominent examples include Exxon Mobil in Nigeria (Global Witness (2016)) or Equatorial Guinea (New York Times (2016)). Even if extractive companies make appropriate market-based payments, government bureaucrats frequently divert extractive revenues away from government ledgers into private offshore accounts. See, for instance, Shell in Nigeria (Global Witness (2017)) or BP in Angola (Global Witness (1999)).

[5]A common way for extractive firms to underreport revenues is to sell commodities to themselves at below market prices such that they pay royalties and taxes on only a fraction of the true value of the resource. See, for example, Sasol in Mozambique (Citi Press (2017)) or Cameco in Canada (Financial Post (2016), CPA Canada (2017)).

[6]Tax terms and royalty rates are provided in national legislation and model contracts. If this is not the case, project-specific extraction terms are often publicly accessible in contract repositories such as `http://resourcecontracts.org`.

shaming can discipline companies not to engage in illicit practices and make higher payments to host governments because of fears that societal pressure could result in a backlash against the firm from customers and investors (Dyck et al. (2008)). In fact, Global Witness, the world's largest activist group against corruption and exploitation in extractive industries, has recently developed a handbook on how to use information contained in extraction payment reports to identify revenue losses (Global Witness (2017)). Tests discussed in this guide include verifying royalty payments based on supplementary data, comparing payment implied commodity prices with international market values, or confirming the government receipt of high risk one-time signature or production bonuses.[7] In contrast, opponents of extraction payment disclosures argue that PGD regulation may have unintended consequences since extraction payment disclosures are currently only effective for European and Canadian firms such that high proprietary costs may induce disclosing companies to cut investment because non-disclosing competitors can use PGD reports to learn about attractive extraction opportunities (e.g., Verrecchia (1983); Darrough and Stoughton (1990); Wagenhofer (1990)).

I use a generalized difference-in-differences design to investigate changes in extractive payments and corporate investment around the introduction of extraction payment disclosures. PGD regulation has several desirable features from a research-design perspective. First, different European countries implemented extraction payment disclosures at different points in time since the regulation was enacted in the form of a European directive and member countries must transpose any European directive into national law within a relatively short, predetermined time window of 2 to 3 years (Christensen et al. (2016)). This staggered adoption allows me to control for concurrent but unrelated market-wide events, which alleviates concerns that my results are spuriously driven by other economic shocks or institutional changes (Leuz and Wysocki (2016)). Second, within any European country, the adoption of PGD regulation across extractive firms depends on the date of the fiscal year end since companies have to publish their payment reports 6 to 11 months

[7]For example, the Natural Resource Governance Institute (NRGI) used Weatherly International's PGD report to detect that the UK mining company did not make royalty payments for two extraction projects in Namibia that had been in production during 2015. NRGI pressured Weatherly International to provide an explanation, which resulted in the payment of additional USD 400,000 since the firm had "overlooked" these royalty obligations (Global Witness (2017)).

after the end of each financial year. One challenge with identifying the causal effects of extraction payment disclosures based on variation in implementation dates between countries is that these dates may not be randomly assigned and that correlated omitted country-level factors could impact legislators' transposition timing (Ball (1980); Mulherin (2007); Christensen et al. (2017)). I address this endogeneity concern by comparing extractive companies that are headquartered within the same country but become subject to PGD regulation at different points in time because of plausibly-exogenous variation in firms' fiscal year ends (similar to Daske et al. (2008)).

I estimate the effects relative to non-disclosing extractive firms from around the world and use coarsened exact matching to construct my control sample based on pre-treatment financial characteristics. All my specifications include natural resource-by-time fixed effects to absorb variation in extractive payments and corporate investment resulting from changes in commodity prices. Moreover, I add foreign country-by-year fixed effects to control for time-varying host country characteristics that could differentially impact my outcome variables across treated and control firms (e.g., GDP growth).

I begin my empirical analysis by investigating the effect of PGD regulation on extractive payments to foreign host countries. To this end, I manually construct a novel dataset covering information on extractive payment practices by multinational oil, gas, and mining firms for 13 host countries before and after extraction payment disclosures become effective. This data differs from the information provided in PGD reports since it is compiled by host countries (not firms) and only available at the firm - host country - year level. The data is not disaggregated by extractive project and type of payment because this information is not available in the pre-PGD disclosure period. In my empirical tests, I investigate the effect of PGD reports on the *coarser* extractive payments that are available both before and after the European Commission introduced PGD regulation.

I document an increase in extractive payments for disclosing companies relative to matched control firms once PGD regulation becomes effective. The coefficient magnitude in my most conservative specification implies that extractive companies increase their transfers to foreign host governments by 0.086 standard deviations once they start preparing extraction payment disclosures. The increase in extractive payments is in line with the notion that disclosing firms engage less in payment avoidance and corrupt business practices since (they anticipate that) interested parties such as NGOs might use the newly available information in PGD reports to identify extractive revenue losses and exert public pressure on them in response.

Next, I examine the impact of PGD regulation on extractive payment gaps. A payment gap is the *relative percentage difference* between the amount that extractive firms send to host governments and the amount that bureaucrats officially book into government ledgers. Payment gaps are highly correlated with corruption measures at the host country level and indicate embezzlement of extractive revenues by government officials (Natural Resource Governance Institute (2017)).[8] I do not find that PGD regulation is significantly associated with reductions in payment gaps, suggesting that extraction payment disclosures are not effective in preventing the diversion of extractive revenues from official government ledgers into private offshore accounts. While NGOs might successfully use extraction payment disclosures to discipline firms by shaming them in their home countries, it is arguably much more difficult for Western activist groups to prevent foreign government officials from misappropriating resource revenues in autocratic and corrupt host countries or to force extractive firms to pass the pressure on to foreign government bureaucrats.

Extraction payment disclosures likely impact firms' investment policies. Since disclosing firms increase their transfers to foreign host governments, the net present value of resource extraction projects declines and affected companies may invest less. Moreover, extraction payment disclosures might impose substantial proprietary costs on disclosing firms since non-disclosing competitors may use the payment reports to learn about profitable extraction opportunities. Disclosing firms may cut investments because of the increased competition for extraction projects and lower ex-post returns on investment (e.g., Verrecchia (1983); Darrough and Stoughton (1990); Wagenhofer (1990)). Consistent with these predictions, I find that European extractive companies cut capital expenditures relative to control firms once PGD regulation becomes effective.[9] I further provide evidence that this

[8]For example, the correlation between extractive payment gaps and the Corruption Perceptions Index by Transparency International (scale from 0 to 100; higher values indicate lower corruption) equals -0.156 (p-value: 0.00).

[9]I document a similar but somewhat weaker decline for disclosing firms' return on assets.

relative decline is driven by the reallocation of investments *across firms* from disclosing companies to unregulated competitors. Moreover, disclosing companies reallocate some investments *within the firm* as they withdraw capital in Africa and (Central) Asia but increase their operational footprint in Latin America. However, the partial substitution of extraction projects between continents is not sufficient to compensate for the overall decline in investments at the consolidated group level.[10]

My difference-in-differences design critically depends on the assumption that the trends in outcome variables for disclosing and non-disclosing firms would have been the same in the absence of PGD regulation (Roberts and Whited (2012)). I assess the validity of this parallel-trends assumption by comparing the evolution of my dependent variables across treated and control firms during the pre-adoption period and find that the trends are virtually identical. Moreover, my outcome variables respond sharply right after extraction payment disclosures become effective, which alleviates the concern that other confounding factors drive the results since remaining omitted variables would need to be correlated with the dependent variable and the entire distribution of PGD adoption dates across European countries and firms, which seems implausible.

Having established my main results, I next provide evidence that the increased threat of public shaming by nonprofit activist groups is a likely channel for the observed real effects. Shaming works particularly well if end consumers purchase directly from extractive companies (e.g. via gas stations) because customers can instantly punish firms for illegitimate actions by not buying their products (BBC (2010); The Telegraph (2010)). Using hand-collected data on the main distribution channel of each extractive firm, I indeed find that the increase in payments and decline in investments is particularly strong for companies that sell their products in direct-to-consumer markets. Moreover, extractive sector NGOs focus their campaigns on large firms because potential rewards to host countries are highest for large scale extraction projects (The Guardian (2015); Independent (2016)) and funding by trusts, foundations, and governments critically depends on successful investiga-

[10] In Sections 4.4 and 5.3, I conduct extensive sensitivity analyses and show that my results are robust to (i) the inclusion of lagged dependent variables (to control for the possibility of mechanical mean reversion), (ii) the exclusion of non-European firms, (iii) different definitions of my dependent variables, (iv) alternative ways of clustering standard errors, and (v) several resource type definitions.

tions that implicate large, well-known companies. Consistent with this campaigning focus, I find that the real effects of extraction payment disclosures are especially pronounced among large companies. Finally, misreporting by extractive companies and collusion with government bureaucrats is arguably worst in corrupt environments (Shleifer and Vishny (1993); Collier (2007)), an argument for which I find somewhat weaker empirical support. While disclosing firms cut slightly more investments in corrupt geographic segments, I do not find differences in payment effects across highly and less corrupt host countries.

Related Literature. I make three contributions relative to the existing literature. First, I add to the literature on CSR reporting, which mainly examines price effects in capital markets.[11] Christensen et al. (2017) study real effects and find that the inclusion of mine safety records in SEC filings is associated with decreases in mining-related citations, injuries, and labor productivity. They document that the increased dissemination of safety issues through financial reports is an important mechanism for their results.[12] In contrast, I investigate the real consequences of social responsibility reporting in a setting where CSR disclosures are published in a separate, stand-alone report and argue that public shaming by NGOs is a likely explanation for the observed real effects. My paper is conceptually related to Dyreng et al. (2016), who also focus on the shaming channel and document that large companies in the United Kingdom engage less in tax avoidance in response to increased pressure by nonprofit activist groups to disclose their subsidiary locations in tax havens. I add to the findings of Dyreng et al. (2016) by providing evidence that public shaming can even impact companies' core economic activities (e.g., investment) and lead to sizeable capital reallocations across and within firms (Hsieh and Klenow (2009); Breuer (2017); Choi (2017); Granja (2017)).

Second, I contribute to the economics and finance literature examining the impact of anticorruption regulation.[13] Several studies find that legislative changes which prohibit

[11] See, for example, Dhaliwal et al. (2011), Ghoul et al. (2011), Servaes and Tamayo (2013), Lys et al. (2015), Friedman and Heinle (2016), Khan et al. (2016), Ioannou and Serafeim (2017), Lins et al. (2017), and Manchiraju and Rajgopal (2017).

[12] Leuz and Wysocki (2016) survey the empirical accounting literature on real effects of disclosure. Kanodia (2006) and Kanodia and Sapra (2016) provide an analytical framework to study real effects of accounting disclosure. Jin and Leslie (2003) and Christensen et al. (2017) study real effects of public information disclosure in non-accounting settings.

[13] Shleifer and Vishny (1993); Bardhan (1997); Svensson (2003) provide surveys of the corruption literature more generally.

the bribery of foreign government officials (e.g., U.S. Foreign Corrupt Practices Act, U.K. Bribery Act, OECD Antibribery Convention) reduce foreign direct investments by Western companies in corrupt countries (Hines (1995); Blundell-Wignall and Roulet (2017); Zeume (2017)). I document similar effects in response to transparency-enhancing anticorruption initiatives and add to the existing literature by focusing on disclosure regulation instead of changes in legal penalties.

Third, I contribute to an emerging literature that examines the economic consequences of mandatory extraction payment disclosures in oil, gas, and mining industries. Healy and Serafeim (2016), Johannesen and Larsen (2016), and Hombach and Sellhorn (2017) document negative abnormal returns for extractive firms around the announcements of PGD regulation in the U.S. and Europe, consistent with investors expecting costly changes in extractive issuers' business activities.[14] I contribute to this literature by examining the ex-post real effects of extraction payment disclosures and the underlying economic mechanism.[15] My results suggest that PGD regulation weakens the competitive position of disclosing firms, which is consistent with the ex-ante reduction in firm value. Moreover, in supplementary tests I do not find that extraction payment disclosures are associated with improved measures of corruption and economic development at the aggregate host country level. Combined, these findings question recent unilateral efforts by large Western countries to address foreign policy objectives by imposing disclosure regulation on only a subset of companies in the global marketplace.

2 Institutional Setting

By nature of their business, extractive companies frequently venture abroad to extract oil, gas, or minerals in foreign host countries that are well endowed with natural resources.

[14] Healy and Serafeim (2016) also document that oil and gas companies almost never voluntarily provided information about payments to foreign host governments in the years leading up to mandatory PGD regulation and that a previous industry self-regulated transparency initiative adopted by host countries is associated with decreases in country corruption ratings.

[15] As an extension, I also investigate liquidity and price effects around the actual publication dates of PGD reports for a subsample of UK extractive firms. I find that PGD disclosures are associated with short-term decreases in information asymmetry (bid-ask spreads) up to one week after the publication of the extraction payment report. In contrast, I do not find significant stock market reactions around the publication dates.

Oil, gas, and mining firms compensate host countries for the resource extraction. Once a company has successfully acquired an extraction license in a foreign host country, an official extraction agreement is set up between the country and the company. This contract specifies the terms of the resource extraction process and governs the official payments that the company makes to the host country. Extractive companies make different kinds of payments, including royalties, license fees, corporate income taxes, production entitlements, and one-time bonuses.[16]

Economists and policymakers are concerned that host countries do not obtain a fair share of extractive sector revenues, thereby limiting the extent to which natural resource endowments stimulate economic development in these nations (Acemoglu and Robinson (2012)). For one, host country officials frequently negotiate corrupt deals with extractive companies (Collier (2007)). The notion is that extractive firms bribe government bureaucrats to receive payment concessions in excess of the illicit kickback (Financial Times (2012)). In this context, even tiny concessions per unit of extracted resource translate into exceptionally high returns to bribery because of nine- or ten-digit extraction volumes in typical oil, gas, and mining projects (Humphreys et al. (2007)). The combination of high returns to bribery, weak institutional environments in many resource rich countries, and frequent interactions with government officials make the extractive sector particularly prone to corruption (EY (2014)). Indeed, the OECD (2014) estimates that 19 percent of all foreign bribery cases occur in the oil, gas, and mining industries, which is higher than in any other sector. For another, government bureaucrats frequently divert extractive revenues away from official government ledgers into private offshore accounts even if extractive companies make appropriate market-based payments. Moreover, extractive companies employ aggressive payment avoidance strategies by underreporting extractive revenues or overreporting project costs (Global Witness (2017)).

In response to these concerns, the European Parliament and EU Council passed new Accounting and Transparency Directives (Directives 2013/34/EU and 2013/50/EU), which

[16] Global Witness (2017) provides a detailed description of each payment type including examples.

require companies in the oil, gas, and mining industries to publicly disclose their payments to foreign host governments in a granular report on their corporate website. Extractive firms also upload the report to the electronic filing platform of their national securities regulator. These disclosure requirements apply to all listed and large, unlisted extractive companies in the European Union, Norway, Iceland, and the United Kingdom. The regulatory objective of these disclosures is to reduce corruption and stimulate economic development in foreign host countries (European Commission (2013)). The idea is that PGD reports allow a wide range of interested parties (e.g., NGOs, civil society) to better monitor extractive activities, identify payments that are "too low" (red flags), and exert public pressure on companies. Once watchdogs expose extractive revenue losses, public shaming can discipline firms not to engage in illicit practices and make higher payments to host countries because of fears that societal pressure could result in a backlash against the firm from customers and investors.

Extractive firms are required to prepare extraction payment disclosures on an annual basis. The reports are almost always published separately from the annual filings on a different date, typically within 6 to 11 months of the firm's fiscal year end. In the report, extractive payments are broken down in detail by (i) the receiving government institution, (ii) extractive project, and (iii) payment type. Audit firms review extraction payment disclosures every year. In 2018, the EU decides whether or not PGD reports will become part of the regular financial statement audit.

Extraction payment reports differ from previously available payment disclosures in two ways. First, information about firm-level extractive payments was dispersed across several reports by different host countries prior to PGD regulation. Specifically, nations that participate in the Extractive Industries Transparency Initiative ("EITI") publish payments by companies that extract natural resources in the given host country on a firm-year basis. In contrast, PGD reports are a one stop information source on extractive payments by a particular company across all host countries the firm operates in. Prior to mandatory extraction payment disclosures, firms did not voluntarily provide payment information, neither in their annual filings nor in separate stand-alone reports (Healy and Serafeim (2016)). Second, the payment information contained in PGD reports is much more disaggregated compared to previous payment disclosures. Unlike before, firm-level payments to governments are not only partitioned by the receiving host country institution, but also by extractive project and payment type. This additional layer of disaggregation is crucial for the monitoring of extractive firms and host governments as it allows interested parties to identify extractive revenue losses.

Policymakers enacted PGD regulation in the form of two European directives in June 2013. Member countries must transpose any European directive into national law within a relatively short, predetermined time window of 2-3 years, which results in country-specific effective dates. However, the regulatory act itself is held constant across jurisdictions. Within a given member country, the adoption of PGD regulation across extractive companies depends on firms' fiscal year ends.

3 Data

3.1 Effective Dates of Extraction Payment Disclosures

I obtain the adoption dates of the staggered roll-out of PGD regulation across Europe from the European Commission. For each member country, I cross-validate the implementation dates with official notifications in federal law gazettes. These notifications specify the entry-into-force dates at which the disclosure directives were transposed into national law and indicate the first fiscal year in which PGD laws became effective for extractive companies that are listed or registered in the particular country. Table 1 summarizes the implementation of PGD regulation across Europe. Extraction payment disclosures first became effective in Norway for fiscal years starting on or after January 1, 2014. The United Kingdom and Romania followed in 2015. In all remaining countries, extraction payment disclosures became mandatory for fiscal years starting on or after January 1, 2016, resulting in an adoption window of three years.[17] Within each country, there is significant variation in the adoption of PGD regulation across extractive firms due to varying fiscal year end dates. For each company in my sample, I verify whether the firm actually prepared a PGD report and manually collect data on the time period it covers.

3.2 Extractive Payments and Payment Reconciliation Data

I obtain micro-level data on extraction payments in foreign host countries from the Extractive Industries Transparency Initiative (hereafter, "EITI"). The EITI is an NGO based in Oslo, Norway, which promotes the open and accountable management of extractive resources through a global standard that host countries can implement. Countries adopt the EITI standard because of better access to international aid and cheaper funding by the International Monetary Fund, the World Bank, and other financial institutions. Once a nation implements the EITI standard, it has to annually deliver an EITI Report, which describes the country's natural resource value chain in detail. This report includes a reconciliation of extractive payments on a firm-year-host country basis, which covers data on (i) payments made by extractive firms and (ii) payments received by the government. The reconciliation is typically reviewed by a big 4 accounting firm, which independently gathers the required payment data from the extractive firms on the one hand and the receiving host government institution on the other hand. The reconciliation covers all extractive companies that are active in a particular host country. If firms refuse to deliver the required data, host countries are required to impose fines on non-complying firms, which include both monetary and reputational penalties. For example, non-complying firms in Liberia are "shamed" by publicly displaying their names and logos on the main streets of

[17] At first sight, the variation in effective dates across Europe might seem limited given that all countries implemented PGD regulation in 2016, except for Norway, the United Kingdom, and Romania. However, there is significantly more variation once one focuses on the importance of each country for the European extractive sector as a whole. In particular, roughly 60% of all European extractive firms are registered or listed in the United Kingdom. Norway is the country with the second highest number of oil, gas, and mining firms (10%). The remaining 30% of extractive firms are evenly spread out across the other European countries.

Monrovia, the country's capital city. As a result, reporting compliance by extractive firms is high, typically above 90%.

I manually collect payment-level data from EITI reconciliation reports for 13 African, Asian, European, and Latin American host countries between 2010 and 2015.[18] Each of the 13 host countries in my sample covers data from extractive companies that are headquartered in Europe, the U.S., Australia, South Africa, China, or other countries.

Adoption of the EITI standard by host countries is voluntary. As a result, corrupt and poorly governed countries might not implement the standard. I assess this potential sample selection issue by comparing the average Transparency International corruption rating of the 13 countries in my sample with its global average (covering 187 countries) and find that they are almost identical and not statistically significant from each other. Nevertheless, the sample could still be selected based on other, potentially unobservable host country characteristics. However, to the extent that the EITI does not cover the most poorly governed countries in which the real effects of extraction payment disclosures are arguably most pronounced, my inferences are conservative as the sample selection biases my estimates towards zero.

3.3 Firm Fundamentals and Host Country Characteristics

I collect financial statement data for listed extractive firms between 2010 and 2017 from Compustat Global, Compustat North America, and Worldscope Geographic Segments. I restrict my analysis to firms with a 2-digit NAICS code of 21 ("Mining, Quarrying, and Oil and Gas Extraction") or a 3-digit NAICS code of 324 ("Petroleum and Coal Products Manufacturing"). Finally, I obtain country-level data on corruption, resource output, governance quality, economic growth, and inflation from Transparency International, the World Bank, and the International Monetary Fund, respectively.

I truncate all continuous and unbounded variables at the 1st and 99th percentile to

[18] Specifically, I obtain micro-level payment data for Azerbaijan, Ethiopia, Ghana, Iraq, Liberia, Mauritania, Myanmar, Norway, Seychelles, Tanzania, Trinidad and Tobago, the United Kingdom, and Zambia.

mitigate the impact of extreme values due to data errors. Tables 2, IA4, and IA5 provide descriptive statistics for my regression variables. In Appendix A1, I define all variables I use in my empirical analysis and indicate their respective data source.

4 Effects on Extractive Payments and Payment Gaps

4.1 Conceptual Underpinnings

I begin my empirical analysis by investigating the relation between PGD regulation and the amount of extractive payments that oil, gas, and mining firms make to foreign host governments.

Policymakers emphasize that extraction payment disclosures facilitate monitoring. The payment information contained in extraction payment disclosures is substantially more disaggregated compared to previously available payment records: Firm-level payments to governments are not only partitioned by the receiving host country institution, but also by extractive project and payment type. This additional layer of disaggregation is crucial for NGOs in monitoring extractive firms and host governments. Previously available information, for example about project-specific extraction quantities and royalty or tax rates, only allowed NGOs to determine the payments that firms should make to host governments (Global Witness (2017)). The missing piece of information was how much companies actually pay to host countries on a project and payment-type level. This information is now publicly available in extraction payment disclosures. As a result, PGD reports empower NGOs to identify payment discrepancies ("red flags") and exert public pressure on extractive firms and corrupt host governments by contacting journalists to encourage media coverage, sending letters to the company and the relevant government institution, asking politicians to raise the issue in parliament, or lobbying anti-corruption agencies to investigate (Dyck et al. (2008)). Once NGOs expose extractive revenue losses, public pressure can discipline firms and governments not to engage in aggressive payment avoidance or corrupt practices, resulting in higher extractive payments for the host country.

Embezzlement of extractive payments by host country bureaucrats is an important type of corruption in natural resource extraction. Specifically, the notion is that government officials who oversee resource revenues pocket a certain amount of the payments made by extractive firms (payment gap). As a result, host countries only receive a fraction of the payments that were initially sent off by oil, gas, and mining firms. PGD reports provide better information to track the trail of money from paying firms to receiving host government institutions. For instance, the detailed payment disaggregation by project and payment type now enables NGOs to cross-verify the government receipt of high risk one-time payments such as signature or production bonuses and thereby prevent the diversion of extractive revenues away from government ledgers into private offshore accounts of the bureaucrats in charge (Global Witness (2017)). The increased detection probability of embezzlement by the politician may result in smaller payment gaps, irrespective of whether the politician substitutes this reduction in private benefits with a different type of corruption that is not visible or detectable via PGD reports. However, if governance structures in foreign host countries are weak (for example in oppressive authoritarian regimes), the additional information contained in extraction payment reports may not help NGOs to hold government officials accountable.

4.2 Empirical Model and Identification Strategy

I use a Difference-in-Differences (DD) estimator to identify the effects of PGD on payment amounts and payment gaps in foreign host countries. The DD research design compares changes in my outcome variables before and after the adoption of PGD regulation across disclosing and not (yet) disclosing firms that extract the same type of natural resource in the same host country in the same year across all host countries. Figure 1 provides a graphical illustration of my identification strategy. Specifically, I examine the impact of disaggregated information provided by PGD disclosures on the coarser extractive payments recorded in EITI reports that are available both before and after the European Commission introduced PGD regulation. I estimate the following OLS regression model:

$$\mathrm{y_{i,hc,t}} = \alpha_{\mathrm{hc,t}} + \alpha_{\mathrm{i(,hc)}} + \alpha_{\mathrm{r,t}} + \beta \cdot \mathrm{PGD_{i,t}} + \gamma' \cdot \mathrm{X_{i,t}} + \epsilon_{\mathrm{i,hc,t}} \quad . \tag{1}$$

The dependent variable $\mathrm{y_{i,hc,t}}$ is either the extractive payment made by firm i to host country hc in year t divided by the firm's lagged total assets or the gap between payments made and payments received by the government, normalized by the former. $\mathrm{PGD_{i,t}}$ is an indicator variable equal to one beginning in the year in which the disclosure regulation becomes effective for the respective European oil, gas, or mining firm. Given the staggered implementation of PGD regulation across Europe, different European extractive firms get treated at different points in time. Non-European companies headquartered in the U.S., Australia, South Africa, China, and other countries do not get treated and serve as an unaffected control group.[19]

$\mathrm{X_{i,t}}$ is a vector of control variables at the parent company level, which includes firm size, the fraction of tangible assets, return on assets, leverage, and Tobin's Q. The staggered adoption of PGD regulation allows me to use (high-dimensional) time fixed effects, which alleviates concerns that my results are driven by concurrent but unrelated market-wide events, such as macroeconomic shocks. Specifically, I include country-by-year fixed effects $\alpha_{\mathrm{hc,t}}$ to control for time-varying host country characteristics (e.g., GDP growth) that could differentially affect my outcome variables across treated and control firms, thereby biasing my inferences. $\alpha_{\mathrm{r,t}}$ conditions the DD design on time-varying trends that are common to each type of natural resource, such as changes in commodity prices. I assign firms to resource types based on their three-digit NAICS industry subsector classification.[20] My classification approach results in resource types such as "Oil and Gas Extraction" (three-

[19]I exclude Canadian firms from my control group since Canada introduced extraction payment disclosures in 2017.

[20]Compustat (Global) specifies the NAICS code for companies headquartered both in and outside of North America.

digit NAICS code 211) or "Mining" (212). In Sections 4.4 and 5.3, I find that my results remain robust when I use a finer resource type definition based on the six-digit NAICS code, which specifies the main natural resource extracted for each firm in my sample (e.g., 212221: "Gold Ore Mining"). Moreover, I add parent or subsidiary fixed effects $\alpha_{\mathrm{i(,hc)}}$ to control for time-invariant firm characteristics (in each host country). As extractive payments by the same firm might be correlated across host countries, I adjust standard errors for within group clusters at the level of the parent company's headquarter country (Bertrand et al. (2004); Petersen (2009)).

4.3 Baseline Results

Table 3 reports the results of regression model (1) for extractive payments. In column (1), I do not control for financial characteristics of the parent company. I find that PGD is strongly positively associated with the amount of extractive payments (coefficient: 0.026; t-statistic: 2.59). Disclosing companies may make higher payments to host governments compared to non-disclosing firms because they operate larger extraction projects (e.g., higher royalties and license fees), have better investment opportunities, or are less financially constrained at the time when PGD regulation becomes effective. To alleviate the concern that my results are spuriously driven by these variables, I control for the parent company's size, fraction of tangible assets, return on assets, leverage, and Tobin's Q.[21] In column (2), I find that the coefficient of PGD remains stable and is not attenuated (coefficient: 0.027; t-statistic: 2.34).[22] A second concern is that imbalances in the empirical distributions of covariates between treated and control firms bias my statistical inferences and introduce model dependence (Ho et al. (2007)). Indeed, in Panel A of Table IA3, I

[21]Due to a lack of data, I cannot control for time-varying project characteristics such as the current stage of the project lifecycle or the yearly extraction volume. The subsidiary fixed effect only conditions on time-invariant project features such as the (average) size of the extraction project. As a result, the magnitude of my estimates needs to be interpreted carefully.

[22]The negative and statistically significant OLS estimate of Return on Assets may seem counterintuitive as it suggests that more profitable extractive companies make smaller payments to host governments. As this estimate is not causally identified, one plausible explanation for the negative association may be that firms which engage in payment avoidance need to make fewer transfers to host governments and thus have a higher return on assets (reverse causality).

document that disclosing extractive firms are substantially larger and more profitable than non-disclosing companies (multivariate L1 distance of 0.822). To improve the estimation of my treatment effects, I coarsen exact match control to disclosing firms based on their size and return on assets in 2013 before the first European country implemented extraction payment disclosures.[23] Panel A of Table IA3 shows that the matching reduces the multivariate covariate imbalance from 0.822 to 0.245. I find that in the coarsened exact matched sample, the estimate of PGD remains statistically significant at the 95th confidence level but becomes smaller (columns (3) and (4) of Table 3). The coefficient magnitude of 0.01 (t-statistic: 2.22) implies that extractive companies increase their transfers to foreign host governments by 0.086 standard deviations (0.01 / 0.116) or £83.86 million once they start disclosing payments in PGD reports. My results are in line with the notion that disclosing firms engage less in payment avoidance and corrupt business practices since (they anticipate that) interested parties such as NGOs use the newly available information in PGD reports to identify extractive revenue losses and exert public pressure on them in response.

One key identifying assumption of my staggered DD design is that payment trends across disclosing and non-disclosing firms would have been the same in the absence of PGD regulation (Roberts and Whited (2012)). In Figure 2, I plot the treatment effects in event time to assess this parallel trends assumption. I find that the coefficients of PGD are close to zero and statistically insignificant in the time periods leading up to the disclosure regulation, suggesting that the parallel trends assumption is satisfied. Moreover, extractive payments increase sharply once PGD regulation becomes effective. Given these treatment dynamics, remaining threats to identification would need to come from omitted variables that are correlated with the entire distribution of PGD effective dates across Europe and concurrent changes in extractive payments. Although this is not impossible, it does not seem to be very likely.

In Table 4, I investigate the impact of PGD regulation on extractive revenue embez-

[23] I restrict the coarsened exact matching to the parent's size and return on assets because (i) these variables are least balanced and (ii) my sample becomes too small if I add more covariates (below 100 observations).

zlement. Both in the full and the coarsened exact matched sample, I find that extraction payment disclosures are not significantly associated with relative payment gaps. The results suggest that PGD reports are not effective in preventing the diversion of extractive revenues from official government ledgers into private offshore accounts of the bureaucrats in charge. NGOs might successfully use extraction payment disclosures to discipline firms by shaming them in their home countries. However, it is arguably much more difficult for Western watchdogs to prevent foreign government officials from misappropriating resource revenues in autocratic and corrupt host countries or to force extractive firms to pass the pressure on to foreign government bureaucrats.

4.4 Robustness

In Table 5, I present several robustness tests for the main results reported in Tables 3 and 4. First, I consider alternative ways to cluster my standard errors. In the baseline specifications, I choose to make conservative inferences and use clusters at the level of the parent company's headquarter country (t-statistics: 2.34 in full sample and 2.43 in CEM sample). To alleviate the concern that the small number of clusters (around 25) leads to an overrejection of the null hypothesis (Bertrand et al. (2004); Cameron and Miller (2015); Imbens and Kolesàr (2016)), I cluster standard errors by 97 parent companies and find that my results are robust (t-statistics: 1.85 and 2.22). Extractive payments are likely autocorrelated within firms since projects are long lived and extraction volumes only change gradually over the project lifecycle. Moreover, unilateral foreign policy measures promoting investment and resource extraction in particular host countries over several years might also result in serially correlated payments. To account for this autocorrelation, I cluster standard errors by 76 home-host country pairs and find that my inferences remain unchanged (t-statistics: 2.22 and 2.44).

Under the second heading of Table 5, I use alternative definitions for my dependent variables. One concern is that the normalization of extractive payments by lagged parent assets may give rise to a spurious positive association with PGD regulation if firms start new projects around the introduction of extraction payment disclosures because payments increase more quickly than total assets percentage-wise. I address this concern by estimating a log-linear model of the amount of extractive payments. The magnitude of the PGD effect becomes larger, in part because the log specification picks up the skewed distribution of extractive payments more easily than the normalized payment variable. Overall, the results and inferences are similar to those in the main analysis. In Table 4, I use the relative payment gap as my dependent variable conditional on the gap being weakly greater than zero. One could argue that this definition of a payment gap is too narrow since extractive firms occasionally report lower payments than receiving host governments to downplay the collaboration with certain countries. In the bottom part of Table 5, I show that my (null) results are robust to a broader payment gap definition that is based on a dummy variable which equals one if firms report higher payments than host governments.

Third, I use a finer industry classification to assign extractive companies to resource types. One potential concern with my baseline empirical model is that the classification based on firms' three-digit NAICS code is relatively coarse and that my resource type-by-time fixed effect does not properly absorb all confounding variation in extractive payments and corporate investment resulting from price changes in individual commodities. I alleviate this concern by using a finer resource type definition based on firms' six-digit NAICS code, which specifies the main natural resource for each parent company in my sample (e.g., 212221: "Gold Ore Mining"). The results mirror those of Table 3 and 4.

4.5 The Shaming Channel

The increase in payments following PGD regulation is consistent with the argument that extraction payment disclosures allow interested parties, particularly NGOs, to publicly expose revenue red flags and thereby discipline extractive companies to make higher transfers to host governments. Specifically, the notion is that management is willing to make higher payments because of fears that public pressure could result in a backlash against the firm from customers and investors. In Table 6, I perform several cross-sectional tests to validate this shaming mechanism.

Shaming works particularly well if end consumers purchase directly from extractive companies (e.g. via gas stations) because they can instantly punish firms for illegitimate actions by not buying their products.[24] In contrast, it is more difficult for consumers to exert pressure if end products only contain certain extractive components that firms sell via wholesale distribution channels because consumers cannot easily distinguish socially responsible from burdened goods. To formally assess this argument, I hand collect data on the main distribution channel of each extractive firm from annual filings. In column (1), I document that the increase in extractive payments is economically more pronounced among companies that sell their products in direct-to-consumer markets (coefficient: 0.032; t-statistic: 2.20) than for firms that distribute via wholesale channels (coefficient: 0.023; t-statistic: 2.00).

Extractive sector NGOs such as Global Witness focus their campaigns on large firms because potential investigation rewards to host countries are highest for large scale extraction projects (The Guardian (2015); Independent (2016)). Moreover, NGOs are commonly resource constrained and continued funding by trusts, foundations, and governments critically depends on successful investigations that generate media attention and implicate large, well-known companies. In contrast, the cost of an investigative campaign is relatively fixed (e.g., salary of campaigner). Consistent with the campaigning focus on large firms, I document that the increase in payments is particularly strong for large extractive companies (coefficient: 0.030; t-statistic: 2.11).

The coefficient differences in these cross-sectional size and product market tests are economically large. However, I aknowledge that they are not statistically significant (p-values of F-tests > 0.10) and readers should therefore interpret these results with caution.

[24]For example, BP faced substantial declines in gasoline sales following consumer boycotts orchestrated by NGOs in response to the Deepwater Horizon oil spill in the Gulf of Mexico in 2010 (BBC (2010); The Telegraph (2010)).

Misreporting by extractive companies and collusion with government bureaucrats is arguably worst in corrupt host countries (Shleifer and Vishny (1993)). If NGOs focus on monitoring extractive activities in corrupt environments, payments should increase more drastically in corrupt nations. However, in column (3) of Table 6, I do not find economically or statistically significant differences in payment increases between highly and less corrupt host countries. One explanation for this null result is that the intensity of NGO monitoring and, more generally, the enforcement environment in firms' home countries is more important for disciplining extractive companies than local conditions abroad. I will investigate and explicitly test for this channel in a future version of my paper.

Analogous to the results in Tables 4 and 5, I do not find that extractive payment gaps are significantly associated with any of the interaction terms in columns (4) to (6).

5 PGD Regulation and Corporate Investment

5.1 Predictions, Empirical Strategy, and Main Results

In this section, I investigate the effects of PGD regulation on corporate investment. Since PGD reports allow interested parties to identify extractive revenue losses and exert public pressure, disclosing firms engage less in payment avoidance and make higher transfers to foreign host governments. As a result, the net present value of resource extraction projects decreases and disclosing companies may invest less. Moreover, extraction payment disclosures might impose substantial proprietary costs on disclosing firms since non-disclosing competitors may use the detailed payment reports to learn about profitable extraction projects and opportunities. Because of the increased competition for extraction projects and lower ex-post returns on investment, disclosing companies may cut investment ex-ante (Verrecchia (1983); Wagenhofer (1990); Aghion and Howitt (1992)).

I adapt my empirical model to study the effects of extraction payment disclosures on quarterly parent-level investments and estimate the following between country DD specification based on the staggered adoption of PGD regulation across Europe:

$$\mathrm{y_{i,t}} = \alpha_\mathrm{i} + \alpha_\mathrm{j,t} + \beta \cdot \mathrm{PGD_{i,t}} + \gamma' \cdot \mathrm{X_{i,t}} + \gamma' \cdot \mathrm{X_{c,t}} + \epsilon_\mathrm{i,t} \quad . \tag{2}$$

The dependent variable $\mathrm{y_{i,t}}$ is the quarterly capital expenditure by extractive company i in quarter t, divided by lagged total assets. $\mathrm{PGD_{i,t}}$ is an indicator variable equal to one beginning in the quarter in which extraction payment disclosures become effective for the particular European oil, gas, or mining firm. I use non-disclosing extractive firms from the U.S., Australia, South Africa, India, and China as a control group.

$\mathrm{X_{i,t}}$ is a vector of balance sheet characteristics, which includes firm size, asset turnover, the fraction of tangible assets, return on assets, leverage, Tobin's Q, and the fraction of liquid assets (cash). $\mathrm{X_{c,t}}$ controls for country-specific macroeconomic conditions and includes the growth rate and lagged level of real GDP, industrial production, and the producer price index. I condition my investment analysis on invariant firm and home country characteristics $\alpha_\mathrm{i/c}$ and include resource type-by-quarter fixed effects $\alpha_\mathrm{j,t}$. I cluster standard errors at the firm instead of the country level since the small number of country clusters (below 20) would otherwise inflate statistical significance (e.g., Cameron and Miller (2015)).

In column (1) of Table 7, I document that the association between extraction payment disclosures and corporate investment is negative but not statistically significant (t-statistic: -1.11). To alleviate concerns that this insignificance is the result of bias due to imbalances in the empirical distributions of covariates between disclosing and control firms (Ho et al. (2007)), I again coarsen exact match my sample based on firms' balance sheet characteristics at the end of 2013. Panel B of Table IA3 reports that this approach significantly improves the match between treatment and control groups as the multivariate covariate imbalance decreases from 0.891 to 0.460. In the coarsened exact matched sample in column (2), I find that the negative estimate of PGD becomes highly statistically significant (t-statistic: -2.94). One plausible explanation for the poor match and null result in the full sample is that disclosing firms are larger and fundamentally different from small, non-disclosing extractive firms. Indeed, in column (3), I find that large disclosing firms invest significantly less than their large, non-disclosing counterparts (coefficient: -0.007; t-statistic: -2.68). In contrast, there is no significant difference in investments between smaller disclosing companies and their non-disclosing benchmark group (coefficient: -0.002; t-statistic: -0.43), which includes a substantial fraction of very small businesses. Once I coarsen exact match the sample in column (4) and thereby remove these small, non-comparable firms, the coefficient of PGD * Mid/Small also becomes significant (coefficient: -0.040; t-statistic: -2.42). Overall, the results in Table 7 suggest that (large) extractive companies invest less relative to unregulated competitors once PGD regulation becomes effective.

Mean reversion in corporate investment is an alternative explanation for the observed empirical pattern and a potential threat to identification. Specifically, extractive firms might heavily invest in foreign host countries using illicit business practices. Given a fixed detection probability, a number of scandals will come to light. As a response, national policymakers might decide to accelerate the implementation of PGD regulation and at the same time investment naturally reverts back to the mean. In this case, extraction payment disclosures would not causally impact investment but rather be associated with it through firms' past investment activities. I examine this possibility in column (5) by controlling for lagged values of corporate investment (lags 1 to 5) and find that my results are virtually unchanged.

More generally, one concern with identifying the causal effects of extraction payment disclosures based on variation in implementation dates across European countries is that these dates are not exogenous and that omitted country-level factors which impact investment could also drive legislators' transposition timing (Christensen et al. (2017); Mulherin (2007)). I address this endogeneity concern by drawing on the fact that within each European country, the adoption of PGD regulation across extractive companies depends on firms' fiscal year end dates since payment reports have to be published within 6 to 11 months of the last financial year. Specifically, I estimate the following within country-year specification, which exploits variation across plausibly-exogenous fiscal year end dates:

$$\mathrm{y_{i,t}} = \alpha_{\mathrm{i}} + \alpha_{\mathrm{j,t}} + \alpha_{\mathrm{c,t}} + \beta \cdot \mathrm{PGD_{i,t}} + \gamma' \cdot \mathrm{X_{i,t}} + \epsilon_{\mathrm{i,t}} \quad . \tag{3}$$

The key difference between specifications (2) and (3) is that I replace my macroeconomic controls with country-by-quarter fixed effects $\alpha_{\mathrm{c,t}}$, which condition the analysis on time-varying, country specific factors that could influence when national legislators decide to transpose PGD regulation.

In Table 8, I report the estimates of my within country-year analysis. I document that my findings are almost identical and slightly stronger than the main results (e.g., coefficient in column (4): -0.044; t-statistic: -3.13), suggesting that my baseline inferences are not spuriously driven by omitted country-level factors.

The key identifying assumption for consistency of my DD estimator is that the average change in corporate investment would have been the same for both the treatment and control groups in the absence of PGD regulation (Roberts and Whited (2012)). While there is no formal test to examine the counterfactual treatment effect, I can assess the validity of this parallel trends assumption. I visualize the estimated treatment effects over my entire sample period by including separate indicators for each quarter before and after extraction payment disclosures become effective, except for quarter t-1 which I use as a benchmark period (Christensen et al. (2017)). In Figure 3, I find that the treatment effects of my within country-year estimator are economically and statistically indistinguishable from zero during the pre-disclosure period, suggesting that the parallel trends assumption is satisfied. Consistent with the results in Table 8, corporate investment drops sharply for large extractive firms in t=0 when extraction payment disclosures become effective, which alleviates the concern that other confounding factors might influence investments and thereby threaten the internal validity of my analysis. The decrease in investments is statistically significant until the end of the sample period. In contrast, small and medium-sized companies do not seem to alter their investment behavior around the onset of the treatment.[25]

In Figure 4, I plot the average residualized capital expenditures from model (3) for large disclosing firms and non-disclosing competitors over time to investigate whether the relative investment decrease is driven by capital reallocations across firms or mere declines in extractive activities by European oil, gas, and mining companies.[26] In order to compare average capital expenditures *within the same calendar quarter* across treatment and control groups, I focus on investment changes around the year 2015 since the majority of European extractive firms became subject to PGD regulation at the beginning of that year.[27] Figure 4 shows that treated firms invest more than their non-disclosing competitors in the years leading up to the disclosure regulation. The similar evolution of average investments in the pre-disclosure period again indicates that the parallel trends assumption is satisfied. However, the investment patterns of both groups reverse as soon as extraction payment disclosures become effective. While disclosing firms reduce their capital expenditures, non-disclosing competitors increase their investment activities. Taken together, this evidence suggests that extraction payment disclosures reallocate investments across firms from disclosing companies to unregulated competitors.

5.2 Investment Profitability

Next, I investigate the impact of extraction payment disclosures on firms' return on assets ("ROA"). PGD regulation disciplines disclosing companies to make higher payments to foreign host countries. As a result, firms retain a lower share of the project's net cash flows and the ROA should decline correspondingly. Before PGD regulation became

[25] In unreported results, I find equivalent treatment dynamics for the between country specification (model (2)).

[26] For ease of exposition, I also normalize average investments by subtracting the mean and dividing by the standard deviation of each group.

[27] My results are virtually identical if I compare investments in event time and use weighted averages to construct synthetic control groups for each quarter.

effective, extractive firms frequently bribed foreign host country bureaucrats to make them accept the underpayment (Global Witness (2017)). Even if companies bribe less in the PGD disclosure regime and make higher official payments to governments, net transfers to host countries likely increased since extractive firms generally engage in corruption to receive payment reliefs in excess of the bribe payments.

In Table 9, I examine the effect of PGD regulation on companies' investment profitability and reestimate my between- (Panel A) and within-country (Panel B) specifications using the quarterly ROA as a dependent variable. Both in the full (column (1)) and the coarsened exact matched sample (column (2)), I do not find that the ROA of disclosing extractive companies changes significantly once PGD regulation becomes effective. However, the average treatment effect hides an interesting cross-sectional heterogeneity. Whereas the ROA of large extractive firms drops significantly by 2 to 3 percentage points per quarter (t-statistics: -2.83 in Panel A-column (3) and -3.37 in Panel B-column (3)), smaller companies do not experience a decline in their investment profitability. These effects get attenuated and become statistically insignificant in the coarsened exact matched sample (column (4)), which could either be the result of a bias-free estimation or the 81% smaller sample. In column (5), I include lagged values of the ROA and find that the results in the full sample are not driven by mean reversion following a surge in profitable extraction projects. Finally, I plot the treatment effects of my ROA regressions in event time (Figure 5) and document event-time dynamics which suggest that the parallel trends assumption is valid. Overall, I find that PGD regulation is negatively associated with the investment profitability of large extractive firms. However, since this result is sensitive to whether I use coarsened exact matching or not, I caution that the evidence should be interpreted carefully.

5.3 Robustness Tests

In Table 10, I assess the sensitivity of the investment and ROA results I presented in Tables 7 to 9. First, I consider alternative sample compositions. In my main sample, 62 of the 67 extractive companies that provide a PGD disclosure list their payments to host governments in a stand-alone report which they publish separately from the annual filings. The remaining five companies (Total, OMV, Galp Energia, Maurel & Prom, and Kenmare Resources) embed extraction payment information into their annual report. I exclude these five firms from the sample to assess whether my inferences are potentially confounded by unrelated information contained in the annual filings of these companies and find that my results are virtually the same. In the main analysis, I use non-European extractive companies that are not directly affected by PGD regulation as a control group. However, my identification strategy relies on the strong assumption that European and non-European extractive firms have parallel investment and ROA trends in the absence of extraction payment disclosures. To alleviate the concern that my DD estimates are biased due to a violation of the parallel trends assumption, I replicate my analysis excluding companies from non-European countries. The results are very similar to those reported in Tables 7 to 9. I further examine the possibility of biased inferences resulting from limited comparability of treatment and control groups across countries by re-estimating the within country-year specification only for extractive firms in the United Kingdom. While the investment effects for large extractive firms remain robust in the UK sample (coefficient: -0.011; t-statistic: -2.20), the ROA results attenuate and become statistically insignificant (coefficient: 0.007; t-statistic: 0.74).

Under the second heading of Table 10, I choose an alternative way to cluster my standard errors. In Tables 7 to 9, I adjust standard errors for within cluster correlation at the firm instead of the home country level because the small number of home country clusters (below 20) could lead to an over rejection of the null hypothesis (see, for example, Cameron and Miller (2015)). For robustness, I do not condition the size of my within country sample on the existence of macroeconomic controls in the between country specifications (which increases the sample to 15,965 observations) and cluster standard errors by 50 headquarter countries. I find that my inferences remain unchanged and that my results get even stronger as the negative, main coefficient of PGD in both the investment and ROA models becomes statistically significant (t-statistics of -2.35 and -2.55).

Third, I use a finer resource type definition based on firms' main natural resource extracted (six-digit NAICS code) to address the concern that the resource type-by-quarter fixed effect in my baseline specification (three-digit NAICS code) is too coarse to absorb all confounding variation resulting from price changes in individual commodities. I find that the investment results are virtually identical. However, the ROA effects attenuate and become statistically insignificant. Overall, my main inferences are robust to a variety of different sampling and research design choices.

5.4 Channels of the PGD-Investment Relation

In Table 11, I perform several cross-sectional tests to uncover the economic mechanism(s) driving the inverse relation between extraction payment disclosures and corporate investment. First, I differentiate whether companies sell their products in direct-to-consumer or wholesale markets. Consistent with the cross-sectional payment results in Section 4.5, I find that the decreases in investments and ROA are concentrated among firms that plausibly increase their extractive payments because they directly cater to end consumers who can punish these companies for illegitimate actions by not buying their products. Again, public shaming seems to be at the heart of these results.

Next, I examine the extent to which the investment effects of PGD regulation depend on the actual publication of extraction payment reports. The public release of payment information is likely instrumental for the disciplining role of PGD regulation for two reasons. For one, interested parties such as NGOs can only use extraction payment reports to identify revenue red flags and exert pressure on firms once the disclosures are out in the public domain. For another, disclosing firms start internalizing the proprietary costs of PGD regulation when payment reports are published and competitors can use the disclosures to learn about profitable extraction projects (Verrecchia (1983); Wagenhofer (1990); Aghion and Howitt (1992)). In contrast, extractive companies may already adjust their payment and investing behavior when PGD regulation becomes effective but before the first report is published because firms anticipate that their (illicit) practices will show up in extraction payment disclosures one year down the road. To assess the relative timing of my investment effects, I add the variable *PGD Published* to specifications (2) and (3), which equals one beginning in the quarter in which the firm publishes its first extraction payment report. In Panel A of Table 11, I find that disclosing firms start cutting investments relative to control firms once extraction payment disclosures enter into force even before these firms release their PGD report (e.g., coefficient of *PGD* in column (3): -0.041; t-statistic: -5.89). The decrease in corporate investment more than doubles after the publication of firms' extraction payment reports (coefficient of *PGD Published*: -0.068; t-statistic: -3.22). In Panel B of Table 11, I document that the relative decline in ROA starts materializing only after the public release of the extraction payment information. Overall, the results of my investment analyses are mainly concentrated in the post-publication period, which is consistent with both a shaming and proprietary cost channel.

While the coefficient differences in my cross-sectional investment analyses are economically sizeable, many of them are not statistically significant. Therefore, readers should interpret this evidence cautiously.

The results in Section 5 suggest that large disclosing firms invest less at the consolidated group level than unregulated competitors once extraction payment disclosures become effective. In Table 12, I reestimate my main tests at the subsidiary level using Worldscope data on extractive investments by geographic segment between 2010 and 2017.[28] The analysis at the geographic segment level allows me to examine the type of host country in

[28] I thank Lisa Yao Liu and Christoph Scheuch for helping me to construct this global segment-level dataset.

which disclosing firms cut investment. Furthermore, the tests help me assess whether disclosing companies partially substitute the investment decrease in one geographic segment with increased investment activities in another segment. I estimate specification (1) using yearly segment-level investments (normalized by lagged segment assets) as the dependent variable.

The results of my segment analysis mirror those of the main regressions. In Table 12, I find that large extractive companies cut segment-level investments by 6.6 percentage points (pp.) once PGD regulation becomes effective (t-statistic in column (3): -3.43). The decrease in investments is economically slightly larger in corrupt (coefficient: -0.068; t-statistic: -2.49) than in less corrupt host countries (coefficient: -0.064; t-statistic: -2.62). In column (5), I document that while disclosing firms move out of Africa (-15.8 pp.) and Asia (-8.4 pp.), they increase their operational footprint in Latin America (+4.6 pp.). Overall, the substitution of projects between continents is not sufficient to compensate the net decrease in investments at the parent company level.

6 Supplementary Analyses

6.1 Exogeneity of PGD Implementation Timing

My identification strategy critically depends on the assumption that the transposition timing of PGD regulation across European countries is random and not driven by omitted variables that are directly or indirectly tied to the behavior of extractive companies (Roberts and Whited (2012)).

One way to assess the exogeneity of PGD's implementation timing across Europe is to investigate what determines the transposition length of the disclosure directive on a country level. I obtain country characteristics as well as implementation details of the Market Abuse and Transparency Directives from Christensen et al. (2016). Moreover, I collect country-specific transposition statistics for all past European directives from the webpages of the European Commission. Similar to Christensen et al. (2016), I find that the time it takes individual European countries to transpose PGD regulation into national law is mainly determined by how fast or slow a country is at transposing directives in general (Table IA1). First, a country's average implementation delay across all previous directives positively predicts PGD transposition length.[29] Second, southern European countries take on average 6 months longer to transpose PGD regulation. Third, the implementation length of past disclosure directives such as the European Transparency Directive of 2007 is weakly, positively associated with the transposition time of PGD regulation. Finally, the importance of a country's extractive sector does not seem to predict the speed of national transposition. Taken together, the results in Table IA1 suggest that countries' implementation timing across different directives is persistent, which is in line with the idea that country-specific effective dates of PGD regulation are plausibly exogenous.

6.2 Aggregate Effects of Extraction Payment Disclosures

One question that still remains unanswered is what are the aggregate effects of extraction payment disclosures for host countries? Does improved monitoring of disclosing firms at the micro-level translate into economic net benefits at the aggregate level or is the effectiveness of PGD regulation limited given that it only applies to European extractive firms? To shed light on this question, I estimate the following within host country OLS model:

$$\mathrm{y_{hc,t}} = \alpha_{\mathrm{hc}} + \alpha_{\mathrm{t}} + \beta \cdot \mathrm{PGD\ Intensity_{i,t}} + \gamma' \cdot \mathrm{X_{hc,t}} + \epsilon_{\mathrm{hc,t}} \quad . \tag{4}$$

My dependent variable $\mathrm{y_{hc,t}}$ is either aggregate oil output, government spending, the corruption perceptions index by Transparency International, or the World Bank's Voice or Regulatory Quality indicators. PGD $\mathrm{Intensity_{hc,t}}$ is the fraction of a host country's total

[29] A country is formally in delay if it did not manage to transpose a given directive into national law within the pre-specified deadline of the European Union. The average implementation delay across all European countries for which I have data equals 10.16 months.

extractive revenues that is subject to payment disclosures. $X_{hc,t}$ is a vector of control variables that includes the ratio of extractive revenues to GDP as well as the natural logarithm of GDP. $\alpha_{h,c}$ conditions my analysis on time-invariant host country characteristics and t controls for global time trends across all countries.

The fraction of a host country's extractive revenues that is subject to disclosure by European oil, gas, and mining firms is not significantly related to the country's oil production (Table IA2). This result is in line with the notion that the reduced investment volume by firms that are subject to PGD regulation is taken over by non-disclosing competitors. Similarly, I do not find that extraction payment disclosures are significantly associated with changes in voice, corruption, or total government spending. In contrast, regulatory quality as measured by the World Bank is positively associated with PGD regulation, which is likely a mechanical result. Finally, I document that extraction payment disclosures are positively related to increased education expenditures, which is weak evidence that PGD regulation improves government monitoring by civil society.

6.3 Capital Market Consequences

In this subsection, I investigate whether extraction payment disclosures impact market liquidity and stock returns once they are published. To this end, I manually collect the publication dates of PGD reports for a subsample of extractive companies that (i) prepared a payment disclosure for 2015 and (ii) are listed on the main market of the London Stock Exchange. Figure IA1 shows that roughly half of the reports were published during the last two days of June, which is due to the fact that the majority of UK extractive firms have their fiscal year end in December and that these companies need to provide their payment disclosures within 6 months of the end of each financial period. The publication dates of the remaining reports are evenly spread out over the year 2016. I merge this data with stock market variables from Datastream and estimate the following OLS regression model:

$$y_{i,t} = \alpha_i + \alpha_t + \beta \cdot \mathrm{PGD}[0,n]_{i,t} + \gamma' \cdot X_{i,t} + \epsilon_{i,t} \quad . \tag{5}$$

The dependent variable is either the natural logarithm of the daily relative bid-ask spread or the firm's daily stock return. PGD[0,n] is an indicator variable which equals one at the publication date of the extraction payment report and n trading days thereafter. In line with prior literature (Chordia et al. (2000); Christensen et al. (2013)), my vector of control variables X contains the natural logarithm of the firm's market value, share turnover, and return variability, lagged by one trading week. α_i conditions my analysis on time-invariant firm characteristics and the trading day fixed effect α_t controls for concurrent but unrelated market-wide events, such as macroeconomic shocks. To account for dependence across observations, I use two-way clustered standard errors at the trading day and firm level.

In Table IA6, I document a decrease in equity bid-ask spreads up to one week following the publication of an extraction payment report. In the full sample, the coefficients are not statistically significant because the day fixed effects absorb most of the variation in *PGD* due to the bunching of extraction payment reports at the end of June. Once I exclude the end of June disclosures, the negative estimates do become significant. The increase in liquidity by 11 to 18 percent is economically meaningful but not too large to be implausible. These results suggest that in the short run PGD reports reduce asymmetric information about extractive payment practices and political risk exposures between the firm and its shareholders or among (informed and uninformed) market participants.[30] In contrast, the coefficient of PGD (indicator variable equal to one beginning at the publication date) indicates that extraction payment disclosures do not persistently reduce bid-ask spreads. Individually published, unaudited PGD reports might simply have too little scope to serve as credible disclosure commitment and thereby reduce information asymmetries in the long

[30] In untabulated results, I investigate several cross-sectional determinants of this relation and find that the decrease in information asymmetry is particularly strong for (complex) firms that are active in many host countries and operate multiple projects per country.

run (Diamond and Verrecchia (1991); Baiman and Verrecchia (1996); Leuz and Verrecchia (2000)).

In Table IA7, I investigate stock price reactions around the publication dates of extraction payment disclosures. Prior literature documents negative abnormal returns for extractive firms upon the announcement of PGD regulation (Hombach and Sellhorn (2017); Healy and Serafeim (2016); Johannesen and Larsen (2016)). In contrast, I do not find significant changes in stock returns once these companies actually publish their payment reports. My findings suggest that, on average, investors did not need to update their beliefs about future expected cash flows since they already correctly anticipated the implications of extraction payment disclosures at the announcement of the regulation.

7 Conclusion

Policymakers increasingly use disclosure regulation to mitigate illegitimate firm behavior and address socio-political policy objectives by requiring firms to publicly provide information about corporate social responsibility. Despite its popularity as a policy tool, we know little about the consequences of CSR disclosures on firms' behavior in the real economy. This paper examines the real effects of mandatory extraction payment disclosures, which require European oil, gas, and mining firms to publicly disclose their payments to foreign host governments in a granular report on their corporate website. I exploit plausibly exogenous variation in the adoption of extraction payment reports across European countries and firms' fiscal year ends to disentangle the disclosure effects from concurrent but unrelated macroeconomic and regulatory changes.

Using manually-collected host country data on firms' extractive activities abroad, I find that disclosing companies increase extractive payments but decrease investments relative to tightly-matched, non-disclosing competitors from around the world. The effects are stronger for firms that sell their products directly to end consumers and for large firms. I further provide evidence that extraction payment disclosures have investment reallocation effects both within and across firms.

My results suggest that social responsibility disclosures can have sizeable real effects, especially if public shaming by specialized activist groups disciplines companies not to engage in illicit practices. In contrast, I do not find that extraction payment disclosures are associated with improved measures of corruption at the aggregate host country level, which casts doubt on recent unilateral efforts by Western countries to address foreign policy objectives by imposing disclosure regulation on only a subset of companies in the global marketplace.

The results of this paper should be interpreted with the following caveats in mind. First, my focus on extraction payment disclosures in the oil, gas, and mining industries may limit the external validity of my findings (Glaeser and Guay (2017)). While the extractive sector setting enables better identification along the causal path, the themes of CSR disclosures and public shaming apply more broadly to other accounting settings. Second, the coefficient differences in my cross-sectional tests are economically sizeable but many times not statistically significant. Therefore, readers should interpret these results with caution. In a future version of this paper, I will extend my post-period sample and isolate the shaming channel more comprehensively in additional cross-sectional tests that focus on the role of media competition and firms' actual media coverage. Third, extraction payment disclosures may generate real effects through channels other than public shaming. For example, the detailed payment information in PGD reports may help European countries to enforce foreign bribery regulation more effectively. I leave the investigation of additional channels to future research.

References

Acemoglu, D. and J. A. Robinson (2012). *Why Nations Fail: The Origins of Power, Prosperity, and Poverty.* Crown Publishers.

Aghion, P. and P. Howitt (1992). A Model of Growth Through Creative Destruction. *Econometrica 60*(2), 323–351.

Baiman, S. and R. E. Verrecchia (1996). The Relation Among Capital Markets, Financial Disclosure, Production Efficiency, and Insider Trading. *Journal of Accounting Research 34*(1), 1–22.

Ball, R. (1980). Discussion of Accounting for Research and Development Costs: The Impact on Research and Development Expenditures. *Journal of Accounting Research 18*, 27–37.

Bardhan, P. (1997). Corruption and Development: A Review of Issues. *Journal of Economic Literature 35*(3), 1320–1346.

BBC (2010). Just How Angry are People at BP? http://www.bbc.com/news/10233882. Accessed: 2017-07-25.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How Much Should We Trust Differences-In-Differences Estimates? *Quarterly Journal of Economics 119*(1), 249–275.

Blundell-Wignall, A. and C. Roulet (2017). Foreign Direct Investment, Corruption and the OECD Anti-Bribery Convention. *OECD Working Papers on International Investment*.

Breuer, M. (2017). How Does Financial Reporting Regulation Affect Market-Wide Resource Allocation? *Working Paper, University of Chicago*, 1–101.

Cameron, C. A. and D. L. Miller (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources 50*(2), 317–373.

Choi, J. H. (2017). Accrual Accounting and Resource Allocation: A General Equilibrium Analysis. *Working Paper, Stanford University*, 1–69.

Chordia, T., A. Subrahmanyam, and R. Roll (2000). Commonality in Liquidity. *Journal of Financial Economics 56*(1), 3–28.

Christensen, H. B., E. Floyd, L. Y. Liu, and M. Maffett (2017). The Real Effects of Mandated Information on Social Responsibility in Financial Reports: Evidence from Mine-Safety Records. *Journal of Accounting and Economics, Forthcoming*.

Christensen, H. B., E. Floyd, and M. Maffett (2017). The Effect of Price Transparency Regulation on Prices in the Healthcare Industry. *Working Paper, University of Chicago*.

Christensen, H. B., L. Hail, and C. Leuz (2013). Mandatory IFRS Reporting and Changes in Enforcement. *Journal of Accounting and Economics 56*(2-3), 147–177.

Christensen, H. B., L. Hail, and C. Leuz (2016). Capital-Market Effects of Securities Regulation: Prior Conditions, Implementation, and Enforcement. *Review of Financial Studies 29*(11), 2885–2924.

Citi Press (2017). Sasol Deal Rips Off Mozambique. http://www.fin24.com/Companies/Industrial/sasol-deal-rips-off-mozambique-20170219-2. Accessed: 2017-06-19.

CNN (2017). House Republicans Look to Roll Back Transparency Law for Energy Companies. Available at: http://edition.cnn.com/2017/01/31/politics/oil-industry-regulations/. Accessed: 2017-05-16.

Collier, P. (2007). *The Bottom Billion: Why the Poorest Countries are Failing and What Can Be Done About It.* Oxford University Press.

CPA Canada (2017). Cameco: Landmark Transfer Pricing Case Begins. https://www.cpacanada.ca/en/connecting-and-news/news/professional-news/2017/january/cameco-landmark-transfer-pricing-case-begins. Accessed: 2017-06-17.

Darrough, M. N. and N. M. Stoughton (1990). Financial Disclosure Policy in an Entry Game. *Journal of Accounting and Economics 12*(1-3), 219–243.

Daske, H., L. Hail, C. Leuz, and R. Verdi (2008). Mandatory IFRS Reporting around the World: Early Evidence on the Economic Consequences. *Journal of Accounting Research 46*(5), 1085–1142.

Dhaliwal, D. S., O. Z. Li, A. Tsang, and Y. G. Yang (2011). Voluntary Nonfinancial Disclosure and the Cost of Equity Capital: The Initiation of Corporate Social Responsibility Reporting. *The Accounting Review 86*(1), 59–100.

Diamond, D. W. and R. E. Verrecchia (1991). Disclosure, Liquidity, and the Cost of Capital. *Journal of Finance 46*(4), 1325–1359.

Dyck, A., N. Volchkova, and L. Zingales (2008). The Corporate Governance Role of the Media: Evidence from Russia. *Journal of Finance 63*(3), 1093–1135.

Dyreng, S. D., J. L. Hoopes, and J. H. Wilde (2016). Public Pressure and Corporate Tax Behavior. *Journal of Accounting Research 54*(1), 147–186.

European Commission (2013). New Disclosure Requirements for the Extractive Industry and Loggers of Primary Forests in the Accounting (and Transparency) Directives - Frequently Asked Questions.

EY (2013). Vision and Priorities of Mary Jo White.

EY (2014). Managing Bribery and Corruption Risks in the Oil and Gas Industry.

Financial Post (2016). Cameco and the CRA Head to Court over Potential CAD 2.2-Billion Tax Dispute. http://business.financialpost.com/news/cameco-and-the-cra-head-to-court-over-potential-2-2-billion-tax-dispute. Accessed: 2017-06-19.

Financial Times (2012). Oil and Gas Has Highest Bribery Rate. Available at: https://www.ft.com/content/c84ead24-ce7e-11e1-bc0c-00144feabdc0. Accessed: 2016-11-29.

Friedman, H. L. and M. S. Heinle (2016). Taste, Information, and Asset Prices: Implications for the Valuation of CSR. *Review of Accounting Studies 21*(3), 740–767.

Fung, A., M. Graham, and D. Weil (2007). *Full Disclosure: The Perils and Promise of Transparency*. Cambridge University Press.

Ghoul, S. E., O. Guedhami, C. C. Kwok, and D. R. Mishra (2011). Does Corporate Social Responsibility Affect the Cost of Capital? *Journal of Banking and Finance 35*(9), 2388–2406.

Glaeser, S. and W. R. Guay (2017). Identification and Generalizability in Accounting Research: A Discussion of Christensen, Floyd, Liu and Maffett (2017). *Journal of Accounting and Economics, Forthcoming*.

Global Witness (1999). A Crude Awakening. https://www.globalwitness.org/en/archive/crude-awakening/. Accessed: 2017-06-17.

Global Witness (2016). Probe into Murky ExxonMobil Deal Shows Why Strong U.S. Transparency Rules are Needed for Oil Companies. https://www.globalwitness.org/en/press-releases/probe-murky-exxonmobil-deal-shows-why-strong-us-transparency-rules-are-needed-oil-companies/. Accessed: 2017-06-19.

Global Witness (2017). The Search for Missing Millions: A Handbook on Turning Payment to Government Transparency into Revenue Accountability.

Granja, J. (2017). Disclosure Regulation in the Commercial Banking Industry: Lessons from the National Banking Era. *Journal of Accounting Research, Forthcoming*.

Healy, P. and G. Serafeim (2016). Voluntary, Self-Regulatory and Mandatory Disclosure of Oil and Gas Company Payments to Foreign Governments. *Working Paper, Harvard University*.

Hines, J. R. J. (1995). Forbidden Payment: Foreign Bribery and American Business After 1977. *NBER Working Paper No. 5266*.

Ho, D. E., K. Imai, G. King, and E. A. Stuart (2007). Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. *Political Analysis 15*(3), 199–236.

Hombach, K. and T. Sellhorn (2017). Financial Disclosure Regulation to Achieve Public Policy Objectives: Evidence from Extractive Issuers. *Working Paper, University of Munich*.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and Manufacturing TFP in China and India. *Quarterly Journal of Economics 124*(4), 1403–1448.

Humphreys, M., J. D. Sachs, and J. E. Stiglitz (2007). *Escaping the Resource Curse*. Columbia University Press.

Iacus, S. M., G. King, and G. Porro (2012). Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis 20*(1), 1–24.

Imbens, G. W. and M. Kolesàr (2016). Robust Standard Errors in Small Samples: Some Practical Advice. *Review of Economics and Statistics 98*(4), 701–712.

Independent (2016). Shell and VW Top List of NGOs Most Hated Brands in the UK. http://www.independent.co.uk/news/business/news/shell-and-vw-top-list-of-ngos-most-hated-brands-in-the-uk-a6818946.html. Accessed: 2017-07-25.

Ioannou, I. and G. Serafeim (2017). The Consequences of Mandatory Corporate Sustainability Reporting. *Working Paper, Harvard University*.

Jin, G. Z. and P. Leslie (2003). The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards. *Quarterly Journal of Economics 118*(2), 409–451.

Johannesen, N. and D. T. Larsen (2016). The Power of Financial Transparency: An Event Study of Country-by-Country Reporting Standards. *Economics Letters 145*, 120–122.

Kanodia, C. (2006). Accounting Disclosure and Real Effects. *Foundations and Trends in Accounting 1*(3), 167–258.

Kanodia, C. and H. Sapra (2016). A Real Effects Perspective to Accounting Measurement and Disclosure: Implications and Insights for Future Research. *Journal of Accounting Research 54*(2), 623–676.

Khan, M., G. Serafeim, and A. Yoon (2016). Corporate Sustainability: First Evidence on Materiality. *The Accounting Review 91*(6), 1697–1724.

Leuz, C. and R. E. Verrecchia (2000). The Economic Consequences of Increased Disclosure. *Journal of Accounting Research 38*, 91–124.

Leuz, C. and P. D. Wysocki (2016). The Economics of Disclosure and Financial Reporting Regulation: Evidence and Suggestions for Future Research. *Journal of Accounting Research 54*(2), 525–622.

Lins, K. V., H. Servaes, and A. Tamayo (2017). Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility During the Financial Crisis. *Journal of Finance 72*(4), 1785–1824.

Lys, T., J. P. Naughton, and C. Wang (2015). Signaling Through Corporate Accountability Reporting. *Journal of Accounting and Economics 60*(1), 56–72.

Manchiraju, H. and S. Rajgopal (2017). Does Corporate Social Responsibility (CSR) Create Shareholder Value? Evidence from the Indian Companies Act 2013. *Journal of Accounting Research, Forthcoming*.

Mulherin, H. J. (2007). Measuring the Costs and Benefits of Regulation: Conceptual Issues in Securities Markets. *Journal of Corporate Finance 13*(2-3), 421–437.

Natural Resource Governance Institute (2017). Twelve Red Flags: Corruption Risks in the Award of Extractive Sector Licenses and Contracts. https://resourcegovernance.org/analysis-tools/publications/twelve-red-flags-corruption-risks-award-extractive-sector-licenses-and. Accessed: 2017-07-28.

New York Times (2016). Under Rex Tillerson, Exxon Mobil Forged Its Own Path Abroad. https://www.nytimes.com/2016/12/13/world/americas/tillersons-company-exxon-mobil-follows-its-own-foreign-policy.html. Accessed: 2017-06-17.

OECD (2014). OECD Foreign Bribery Report: An Analysis of the Crime of Bribery of Foreign Public Officials. Available at: http://www.oecd.org/corruption/oecd-foreign-bribery-report-9789264226616-en.htm. Accessed: 2017-07-28.

Open Oil (2012). Oil Contracts - How to Read and Understand Them. Available at: http://openoil.net/understanding-oil-contracts/. Accessed: 2017-09-06.

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies 22*(1), 435–480.

Resource Contracts (2014). Mining Contracts - How to Read and Understand Them. Available at: http://www.resourcecontracts.org/page/resources. Accessed: 2017-09-06.

Roberts, M. R. and T. M. Whited (2012). Endogeneity in Empirical Corporate Finance. *Handbook of the Economics of Finance 2*.

Servaes, H. and A. Tamayo (2013). The Impact of Corporate Social Responsibility on Firm Value: The Role of Customer Awareness. *Management Science 59*(5), 1045–1061.

Shleifer, A. and R. W. Vishny (1993). Corruption. *Quarterly Journal of Economics 108*(3), 599–617.

Svensson, J. (2003). Who Must Pay Bribes and How Much? Evidence from a Cross Section of Firms. *Quarterly Journal of Economics 118*(1), 207–230.

The Guardian (2015). Under Pressure: Campaigns that Persuaded Companies to Change the World. https://www.theguardian.com/sustainable-business/2015/feb/09/corporate-ngo-campaign-environment-climate-change. Accessed: 2017-07-25.

The Telegraph (2010). Gulf of Mexico Oil Spill: BP Faces Growing Calls for Boycott of its US Products . http://www.telegraph.co.uk/finance/newsbysector/energy/oilandgas/7742471/Gulf-of-Mexico-oil-spill-BP-faces-growing-calls-for-boycott-of-its-US-products.html. Accessed: 2017-07-25.

Verrecchia, R. E. (1983). Discretionary Disclosure. *Journal of Accounting and Economics 5*, 179–194.

Wagenhofer, A. (1990). Voluntary Disclosure with a Strategic Opponent. *Journal of Accounting and Economics 12*(4), 341–363.

Zeume, S. (2017). Bribes and Firm Value. *Review of Financial Studies 30*(5), 1457–1489.

Tables and Figures

Table 1: EU/EEA Implementation of Extraction Payment Disclosures

Country	PGD Entry-Into-Force Date	Applicable For Fiscal Years Starting On/After	Unique Extractive Firms	N Extractive Firms	Mean Fiscal Year End Month	Std. Dev. Fiscal Year End Month
Austria	Jul 20, 2015	Jan 01, 2016	4	73	11.63	0.99
Belgium	Jan 01, 2016	Jan 01, 2016	2	21	12.00	0.00
Bulgaria	Jan 01, 2016	Jan 01, 2016	0	0	n.a.	n.a.
Croatia	Jan 01, 2016	Jan 01, 2016	1	29	12.00	0.00
Cyprus	n.a.	n.a.	5	126	11.60	1.02
Czech Republic	Jan 01, 2016	Jan 01, 2016	2	46	12.00	0.00
Denmark	Jul 01, 2015	Jan 01, 2016	2	37	12.00	0.00
Estonia	Jan 01, 2016	Jan 01, 2016	0	0	n.a.	n.a.
Finland	Jan 01, 2016	Jan 01, 2016	0	0	n.a.	n.a.
France	Oct 29, 2015	Jan 01, 2016	14	271	11.67	1.57
Germany	Jul 23, 2015	Jan 01, 2016	14	300	11.43	1.61
Greece	Jul 07, 2016	n.a.	7	160	12.00	0.00
Hungary	Jan 01, 2016	Jan 01, 2016	2	24	12.00	0.00
Iceland	Jan 01, 2016	Jan 01, 2016	0	0	n.a.	n.a.
Ireland	n.a.	n.a.	15	387	10.55	2.72
Italy	Jan 01, 2016	Jan 01, 2016	6	144	12.00	0.00
Latvia	Jan 01, 2016	Jan 01, 2016	1	9	12.00	0.00
Liechtenstein	Aug 01, 2015	Jan 01, 2016	0	0	n.a.	n.a.
Lithuania	Jul 01, 2015	Jan 01, 2016	0	0	n.a.	n.a.
Luxembourg	Dec 18, 2015	Jan 01, 2016	3	40	11.45	2.42
Malta	Jan 01, 2016	Jan 01, 2016	0	0	n.a.	n.a.
Netherlands	Nov 10, 2015	Jan 01, 2016	4	106	12.00	0.00
Norway	Jan 01, 2014	Jan 01, **2014**	51	972	12.00	0.00
Poland	Sep 23, 2015	Jan 01, 2016	11	234	12.00	0.00
Portugal	May 26, 2015	Jan 01, 2016	1	28	12.00	0.00
Romania	Jan 01, 2015	Jan 01, **2015**	9	169	12.00	0.00
Slovakia	Jul 01, 2015	Jan 01, 2016	2	49	12.00	0.00
Slovenia	Jan 01, 2016	Jan 01, 2016	0	0	n.a.	n.a.
Spain	Jan 01, 2016	Jan 01, 2016	3	49	12.00	0.00
Sweden	Jul 20, 2015	Jan 01, 2016	34	781	11.92	0.54
Switzerland	n.a.	n.a.	7	127	11.91	0.97
United Kingdom	Dec 01, 2014	Jan 01, **2015**	291	6310	9.76	3.29

Table 2: Descriptive Statistics

This table reports descriptive statistics for key variables of my empirical analysis. I report the number of observations (N), mean, standard deviation (SD), 10% quantile (p10), 25% quantile (p25), median (p50), 75% quantile (p75), and 90% quantile (p90). Panel A provides statistics for the variables used in the payment (gap) regressions. Panel B reports summary statistics for the variables used in the investment and RoA analyses. I define all variables in Table A1. I obtain payment data from the *Extractive Industries Transparency Initiative (EITI).* I retrieve the implementation dates of PGD regulation across Europe from the homepage of the *European Commission.* I collect firm fundamentals from *Compustat* and macroeconomic variables from the *International Monetary Fund.* This sample covers oil, gas, and mining companies during the time period 2010 to 2017.

Panel A: Variables used in Payment (Gap) Regressions

	N	Mean	SD	p10	p25	p50	p75	p90
PGD	881	0.064	0.244	0.000	0.000	0.000	0.000	0.000
Extractive Payment (/TA_{t-1})	881	0.031	0.116	0.000	0.000	0.001	0.011	0.059
Extractive Payment (£ mn.)	881	343.720	975.223	0.000	0.553	7.893	126.503	1065.713
Payment Gap	498	0.057	0.131	0.000	0.000	0.001	0.045	0.186
Ln(Total Assets)	881	9.225	2.760	4.911	7.392	10.015	11.506	12.190
PPE	881	0.530	0.198	0.307	0.405	0.527	0.689	0.806
Return on Assets	881	0.091	0.160	-0.066	0.060	0.114	0.170	0.225
Leverage	881	0.209	0.131	0.019	0.124	0.206	0.294	0.378
Q	881	1.426	1.457	0.636	0.814	1.031	1.423	2.307

Panel B: Variables used in Investment and RoA Regressions

	N	Mean	SD	p10	p25	p50	p75	p90
PGD	8153	0.025	0.157	0.000	0.000	0.000	0.000	0.000
Investments	8153	0.035	0.045	0.001	0.007	0.020	0.046	0.084
Return on Assets	8153	-0.020	0.121	-0.131	-0.024	0.017	0.038	0.057
Ln(Total Assets)	8153	5.590	2.998	1.405	3.444	5.942	7.693	9.092
Asset Turnover	8153	0.103	0.118	0.000	0.034	0.071	0.126	0.229
PPE	8153	0.638	0.250	0.250	0.495	0.693	0.839	0.912
Leverage	8153	0.362	0.544	0.002	0.117	0.269	0.432	0.685
Q	8153	3.176	10.150	0.747	0.979	1.320	2.081	4.396
Cash	8153	0.113	0.166	0.004	0.016	0.054	0.132	0.290

Table 3: Effect of PGD Regulation on Extractive Payments

This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on payments to foreign host governments by European oil, gas, and mining companies (model (1)). The dependent variable *Extractive Payment / Total Assets$_{t-1}$* is the ratio of a firm's payments to a given host government in a given year divided by the parent company's lagged total assets. The key explanatory variable *PGD* is an indicator equal to one beginning in the year in which PGD regulation becomes effective for the given extractive subsidiary. *Ln(Total Assets)* is defined as the natural logarithm of the parent company's total assets. *PPE* is the ratio of the parent company's net plant, property, and equipment to total assets. *Return on Assets* is defined as the parent company's operating income before depreciation divided by lagged total assets. *Leverage* is the ratio of the parent company's long-term debt plus debt in current liabilities to total assets. *Q* is defined as the sum of the parent company's market capitalization and book value of liabilities divided by total assets. In columns (1) and (2), I estimate the OLS model for the full sample and in columns (3) and (4) I use the coarsened exact matched sample. All specifications include host country-by-year, resource type-by-year (where resource types are defined using the 3-digit NAICS code), and subsidiary fixed effects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the parent company's headquarter country. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Extractive Payment / Total Assets$_{t-1}$			
	(1)	(2)	(3)	(4)
PGD	0.026**	0.027**	0.011**	0.010**
	(2.59)	(2.34)	(2.49)	(2.43)
Ln(Total Assets)		0.002		0.015
		(0.53)		(1.33)
PPE		0.009		-0.024
		(0.44)		(-0.72)
Return on Assets		-0.053***		-0.116*
		(-3.01)		(-1.96)
Leverage		-0.043		-0.116**
		(-1.10)		(-2.89)
Q		0.002		0.001*
		(1.06)		(1.78)
Observations	855	791	386	350
Adjusted R-Squared	0.889	0.895	0.834	0.842
Host Country × Year FE	Yes	Yes	Yes	Yes
Resource Type × Year FE	Yes	Yes	Yes	Yes
Subsidiary FE	Yes	Yes	Yes	Yes
Sample	Full	Full	Coarsened Exact Matching (CEM)	
Cluster Level	HQ Country	HQ Country	HQ Country	HQ Country
Number of Clusters	30	27	22	18

Table 4: Effect of PGD Regulation on Payment Gaps
This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on payment gaps (model (1)). The dependent variable *Payment Gap* is the difference between payments made by an extractive subsidiary and the corresponding payments officially received by the host government in a given year, divided by the former. The key explanatory variable *PGD* is an indicator equal to one beginning in the year in which PGD regulation becomes effective for the given extractive subsidiary. *Ln(Total Assets)* is defined as the natural logarithm of the parent company's total assets. *PPE* is the ratio of the parent company's net plant, property, and equipment to total assets. *Return on Assets* is defined as the parent company's operating income before depreciation divided by lagged total assets. *Leverage* is the ratio of the parent company's long-term debt plus debt in current liabilities to total assets. *Q* is defined as the sum of the parent company's market capitalization and book value of liabilities divided by total assets. In columns (1) and (2), I estimate the OLS model for the full sample and in columns (3) and (4) I use the coarsened exact matched sample. All specifications include host country-by-year, resource type-by-year (where resource types are defined using the 3-digit NAICS code), and subsidiary fixed effects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the parent company's headquarter country. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Payment Gap / Extractive Payment			
	(1)	(2)	(3)	(4)
PGD	0.027	0.010	0.084	0.133
	(1.48)	(0.87)	(0.76)	(0.90)
Ln(Total Assets)		-0.015		-0.013
		(-0.80)		(-0.12)
PPE		0.181*		0.745*
		(1.93)		(2.13)
Return on Assets		0.058		0.237
		(0.82)		(0.33)
Leverage		0.019		-1.072***
		(0.16)		(-3.37)
Q		-0.004		-0.015
		(-0.67)		(-0.69)
Observations	434	395	169	152
Adjusted R-Squared	0.277	0.326	0.776	0.812
Host Country × Year FE	Yes	Yes	Yes	Yes
Resource Type × Year FE	Yes	Yes	Yes	Yes
Subsidiary FE	Yes	Yes	Yes	Yes
Sample	Full	Full	Coarsened Exact Matching (CEM)	
Cluster Level	HQ Country	HQ Country	HQ Country	HQ Country
Number of Clusters	26	23	16	14

Table 5: Robustness - Payment (Gap) Regressions

This table summarizes the sensitivity of my payment (gap) results. I reestimate model (1) but use different definitions for my dependent variables and cluster standard errors in several alternative ways. In the first column, I describe each robustness test. N equals the number of observations and PGD is the OLS coefficient of my main variable of interest. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Robustness Test	N	PGD
1. Alternative Clustering		
Extractive Payments		
– Table 3 (2) Baseline: Clustering by HQ country	791	0.027**
		(2.34)
– Table 3 (2) Clustering by parent	791	0.027*
		(1.85)
– Table 3 (2) Clustering by home-host country pair	791	0.027**
		(2.22)
– Table 3 (4) Baseline CEM: Clustering by HQ country	350	0.010**
		(2.43)
– Table 3 (4) CEM: Clustering by parent	350	0.010**
		(2.22)
– Table 3 (4) CEM: Clustering by home-host country pair	350	0.010**
		(2.44)
Payment Gaps		
– Table 4 (2) Baseline: Clustering by HQ country	395	0.010
		(0.87)
– Table 4 (2) Clustering by parent	395	0.010
		(0.50)
– Table 4 (2) Clustering by home-host country pair	395	0.010
		(0.46)
– Table 4 (4) Baseline CEM: Clustering by HQ country	152	0.133
		(0.90)
– Table 4 (4) CEM: Clustering by parent	152	0.133
		(0.88)
– Table 4 (4) CEM: Clustering by home-host country pair	152	0.133
		(0.89)
2. Alternative Dependent Variable		
Extractive Payments		
– Table 3 (2): Ln(1+Extractive Payment)	793	0.702
		(1.15)
– Table 3 (4) CEM: Ln(1+Extractive Payment)	350	1.553*
		(2.11)
Payment Gaps		
– Table 4 (1): $\mathbb{1}_{\text{Payment Gap}>0}$	1,023	-0.038
		(-0.57)
– Table 4 (2): $\mathbb{1}_{\text{Payment Gap}>0}$	941	-0.042
		(-0.63)
– Table 4 (3) CEM: $\mathbb{1}_{\text{Payment Gap}>0}$	392	-0.083
		(-0.86)
– Table 4 (4) CEM: $\mathbb{1}_{\text{Payment Gap}>0}$	392	-0.083
		(-0.46)
3. Alternative Resource Type Definition		
Extractive Payments		
– Table 3 (2): 6-Digit NAICS Code	759	0.031**
		(2.38)
Payment Gaps		
– Table 4 (2): 6-Digit NAICS Code	380	0.008
		(0.58)

Table 6: Channels of the PGD-Payment Relation

This table reports the coefficients of OLS regressions investigating the economic channel behind the effects of PGD regulation on extractive payments and payment gaps (model (1)). The dependent variable in columns (1) to (3) is the ratio of a firm's payments to a given host government in a given year divided by the parent company's lagged total assets (*Extractive Payment / Total Assets$_{t-1}$*). The outcome variable in columns (4) to (6) is the difference between payments made by an extractive subsidiary and the corresponding payments officially received by the host government in a given year, divided by the former (*Payment Gap*). The key explanatory variable *PGD* is an indicator equal to one beginning in the year in which PGD regulation becomes effective for the given extractive subsidiary. *Large (Mid/Small)* is an indicator variable equal to one if the parent company's average assets exceed (are below) their 66th percentile value. *Higher (Lower)* Corruption is a dummy variable equal to one if the Corruption Perceptions Index (CPI) of a given host country is higher (lower) than the median CPI in the given year. *Direct-to-Consumer (Wholesale)* is an indicator variable equal to one if the extractive firm sells its products directly to end consumers (in wholesale markets). All specifications include parent company controls and host country-by-year, resource type-by-year (where resource types are defined using the 3-digit NAICS code), as well as subsidiary fixed effects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the parent company's headquarter country. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Extractive Payment / Total Assets$_{t-1}$			Payment Gap / Extractive Payment		
	(1)	(2)	(3)	(4)	(5)	(6)
PGD * Direct-to-Consumer	0.032**			-0.014		
	(2.20)			(-0.98)		
PGD * Wholesale	0.023*			0.033		
	(2.00)			(1.23)		
PGD * Large		0.030**			-0.002	
		(2.11)			(-0.18)	
PGD * Mid/Small		0.024**			0.028	
		(2.32)			(1.48)	
PGD * Higher Corruption			0.022*			-0.011
			(1.73)			(-0.81)
PGD * Lower Corruption			0.029			0.023
			(1.48)			(1.35)
Observations	791	791	791	395	395	395
Adjusted R-Squared	0.895	0.895	0.895	0.324	0.324	0.324
F-Test: ΔCoefficients (p-value)	0.400	0.309	0.793	0.182	0.136	0.105
Parent Controls	Yes	Yes	Yes	Yes	Yes	Yes
Host Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Resource Type × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Subsidiary FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full	Full
Cluster Level	Parent Headquarter Country			Parent Headquarter Country		
Number of Clusters	27	27	27	23	23	23

Table 7: Effect of PGD Regulation on Investments

This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on parent-level investments by European oil, gas, and mining companies (model (2)). *Investments* is defined as capital expenditures divided by lagged book assets. The key explanatory variable *PGD* is an indicator equal to one beginning in the quarter in which PGD regulation becomes effective for the given extractive company. *Large (Mid/Small)* is an indicator variable equal to one if the parent company's average assets exceed (are below) their 66th percentile value. *Ln(Total Assets)* is the natural logarithm of total assets. *Asset Turnover* is defined as the ratio of quarterly sales to total assets. *PPE* equals net plant, property, and equipment divided by total assets. *Return on Assets* is defined as operating income before depreciation divided by lagged book assets. *Leverage* equals long-term debt plus debt in current liabilities divided by total assets. *Q* is the sum of the firm's market capitalization and book value of liabilities divided by total assets. *Cash* is defined as the ratio of cash and short-term investments to total assets. All specifications include resource type-by-quarter fixed effects (where resource types are defined using the 3-digit NAICS code), firm fixed effects, (home) country fixed effects, and macroeconomic controls. In columns (1), (3), and (5), I estimate the OLS model for the full sample and in columns (2) and (4) I use the coarsened exact matched sample. In column (5), I control for lagged dependent variables to assess whether my results are driven by mechanical mean reversion following the adoption of extraction payment disclosures in response to a wave of scandalous but profitable extraction projects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the extractive company. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Investments / Total Assets$_{t-1}$				
	(1)	(2)	(3)	(4)	(5)
PGD	-0.004	-0.040***			
	(-1.11)	(-2.94)			
PGD * Large			-0.007***	-0.040***	-0.007***
			(-2.68)	(-4.07)	(-3.47)
PGD * Mid/Small			-0.002	-0.040**	-0.004
			(-0.43)	(-2.42)	(-1.10)
Ln(Total Assets)	0.005**	0.011***	0.005**	0.011***	-0.001
	(2.38)	(3.04)	(2.38)	(3.04)	(-0.62)
Asset Turnover	0.009	-0.007	0.009	-0.007	-0.003
	(0.96)	(-0.31)	(0.93)	(-0.31)	(-0.24)
PPE	0.024***	0.003	0.025***	0.003	0.026***
	(4.14)	(0.12)	(4.15)	(0.12)	(2.72)
Return on Assets	-0.022*	0.040	-0.022*	0.040	-0.013
	(-1.85)	(1.18)	(-1.86)	(1.18)	(-0.73)
Leverage	-0.003**	0.000	-0.003**	0.000	-0.005**
	(-2.46)	(0.17)	(-2.46)	(0.17)	(-2.02)
Q	0.000	-0.000	0.000	-0.000	-0.000
	(1.24)	(-0.30)	(1.22)	(-0.29)	(-0.67)
Cash	0.015*	-0.024	0.015*	-0.025	0.007
	(1.86)	(-0.89)	(1.87)	(-0.89)	(0.67)
Observations	8,096	1,565	8,096	1,565	4,762
Adjusted R-Squared	0.425	0.605	0.425	0.604	0.511
F-Test: ΔPGD Coefficients (p-value)	-	-	0.201	0.958	0.450
Macro Controls	Yes	Yes	Yes	Yes	Yes
Lagged Dependent Variables	No	No	No	No	Yes
HQ Country FE	Yes	Yes	Yes	Yes	Yes
HQ Country × Quarter FE	No	No	No	No	No
Resource Type × Quarter FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Sample	Full	CEM	Full	CEM	Full
Cluster Level	Firm	Firm	Firm	Firm	Firm
Number of Clusters	583	172	583	172	449

Table 8: PGD Regulation and Investments – Within Country-Year Estimator
This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on parent-level investments using within country-year specifications (model (3)). *Investments* is defined as capital expenditures divided by lagged book assets. The key explanatory variable *PGD* is an indicator equal to one beginning in the quarter in which PGD regulation becomes effective for the given extractive company. *Large (Mid/Small)* is an indicator variable equal to one if the parent company's average assets exceed (are below) their 66th percentile value. All specifications include (home) country-by-quarter fixed effects, resource type-by-quarter fixed effects (where resource types are defined using the 3-digit NAICS code), firm fixed effects, and financial controls. In columns (1), (3), and (5), I estimate the OLS model for the full sample and in columns (2) and (4) I use the coarsened exact matched sample. In column (5), I control for lagged dependent variables to assess whether my results are driven by mechanical mean reversion following the adoption of extraction payment disclosures in response to a wave of scandalous but profitable extraction projects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the extractive company. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Investments / Total Assets$_{t-1}$				
	(1)	(2)	(3)	(4)	(5)
PGD	-0.005	-0.044***			
	(-1.14)	(-3.13)			
PGD * Large			-0.010***	-0.047***	-0.011***
			(-2.80)	(-5.12)	(-3.43)
PGD * Mid/Small			-0.003	-0.043***	-0.007
			(-0.59)	(-2.71)	(-1.54)
Observations	8,048	1,544	8,048	1,544	4,720
Adjusted R-Squared	0.418	0.618	0.418	0.618	0.506
F-Test: ΔPGD Coefficients (p-value)	-	-	0.100	0.721	0.370
Firm Controls	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	No
Lagged Dependent Variables	No	No	No	No	Yes
HQ Country FE	No	No	No	No	No
HQ Country × Quarter FE	Yes	Yes	Yes	Yes	Yes
Resource Type × Quarter FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Sample	Full	CEM	Full	CEM	Full
Cluster Level	Firm	Firm	Firm	Firm	Firm
Number of Clusters	582	170	582	170	445

Table 9: Effect of PGD Regulation on Return on Assets

This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on return on assets at the parent level (models (2) and (3)). *Return on Assets* is defined as operating income before depreciation divided by lagged book assets. The key explanatory variable *PGD* is an indicator equal to one beginning in the quarter in which PGD regulation becomes effective for the given extractive company. *Large (Mid/Small)* is an indicator variable equal to one if the parent company's average assets exceed (are below) their 66th percentile value. All specifications include resource type-by-quarter fixed effects (where resource types are defined using the 3-digit NAICS code), firm fixed effects, and financial controls. In Panel A, I report the coefficients of my *between country* specifications to which I add country fixed effects and macroeconomic controls. In Panel B, I report the results of my *within country-year* models in which I use country-by-quarter fixed effects (instead of country fixed effects and macro controls). In columns (1), (3), and (5), I estimate the OLS model for the full sample and in columns (2) and (4) I use the coarsened exact matched sample. In column (5), I control for lagged dependent variables to assess whether my results are driven by mechanical mean reversion following the adoption of extraction payment disclosures in response to a wave of scandalous but profitable extraction projects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the extractive company. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Between Country Models

	Return on Assets				
	(1)	(2)	(3)	(4)	(5)
PGD	-0.003	0.010			
	(-0.40)	(0.48)			
PGD * Large			-0.020***	-0.004	-0.013*
			(-2.83)	(-0.16)	(-1.88)
PGD * Mid/Small			0.006	0.015	-0.002
			(0.71)	(0.70)	(-0.22)
Observations	8,096	1,565	8,096	1,565	4,438
Adjusted R-Squared	0.629	0.694	0.629	0.694	0.620
F-Test: ΔPGD Coefficients (p-value)	-	-	0.004	0.372	0.153
Firm Controls	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes
Lagged Dependent Variables	No	No	No	No	Yes
HQ Country FE	Yes	Yes	Yes	Yes	Yes
HQ Country $\times$ Quarter FE	No	No	No	No	No
Resource Type $\times$ Quarter FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Sample	Full	CEM	Full	CEM	Full
Cluster Level	Firm	Firm	Firm	Firm	Firm
Number of Clusters	583	172	583	172	430

Panel B: Within Country-Year Models

	Return on Assets				
	(1)	(2)	(3)	(4)	(5)
PGD	-0.005	0.014			
	(-0.54)	(0.65)			
PGD * Large			-0.030***	0.003	-0.023**
			(-3.37)	(0.13)	(-2.45)
PGD * Mid/Small			0.004	0.016	-0.009
			(0.40)	(0.73)	(-0.99)
Observations	8,048	1,544	8,048	1,544	4,394
Adjusted R-Squared	0.625	0.698	0.625	0.698	0.617
F-Test: ΔPGD Coefficients (p-value)	-	-	0.000	0.466	0.090
Firm Controls	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	No
Lagged Dependent Variables	No	No	No	No	Yes
HQ Country FE	No	No	No	No	No
HQ Country $\times$ Quarter FE	Yes	Yes	Yes	Yes	Yes
Resource Type $\times$ Quarter FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Sample	Full	CEM	Full	CEM	Full
Cluster Level	Firm	Firm	Firm	Firm	Firm
Number of Clusters	582	170	582	170	425

Table 10: Robustness - Investment and RoA Regressions
This table summarizes the sensitivity of my investment and RoA results. I reestimate models (2) and (3) but use different sample specifications and cluster standard errors in several alternative ways. In the first column, I describe each robustness test. *N* is the number of observations and *PGD*, *PGD*Large*, and *PGD*Mid/Small* are the OLS coefficients of my main variables of interest. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Between Country-Year (Tables 7 and 9A)			*Within Country-Year (Tables 8 and 9B)*		
	PGD	PGD*Large	PGD*Mid/Small	PGD	PGD*Large	PGD*Mid/Small
1. Alternative Sample Specifications						
Investments						
– PGD report separate from annual filings	-0.003	-0.007**	-0.001	-0.005	-0.010***	-0.003
(N = 8,048)	(-0.84)	(-2.52)	(-0.21)	(-1.08)	(-2.74)	(-0.53)
– Excluding non-European countries	-0.005	-0.010***	-0.003	-0.004	-0.010**	-0.002
(N = 1,420)	(-1.54)	(-3.13)	(-0.67)	(-1.07)	(-2.37)	(-0.51)
– Including only the United Kingdom				-0.004	-0.011**	-0.002
(N = 1,093)				(-1.00)	(-2.20)	(-0.48)
Return on Assets						
– PGD report separate from annual filings	-0.001	-0.018**	0.007	-0.005	-0.029***	0.004
(N = 8,048)	(-0.18)	(-2.54)	(0.76)	(-0.49)	(-3.14)	(0.36)
– Excluding non-European countries	-0.009	-0.012*	-0.007	-0.006	-0.010	-0.004
(N = 1,420)	(-1.50)	(-1.76)	(-1.10)	(-0.86)	(-1.47)	(-0.58)
– Including only the United Kingdom				-0.004	0.007	-0.007
(N = 1,019)				(-0.59)	(0.74)	(-0.91)
2. Alternative Clustering						
Clustering at HQ Country (all/50 countries)						
– Investments				-0.004**	-0.006*	-0.002***
(N = 15,965)				(-2.35)	(-1.74)	(-3.29)
– Return on Assets				-0.007**	-0.020***	0.002
(N = 15,965)				(-2.55)	(-3.42)	(0.39)
3. Alternative Resource Type Definition						
6-Digit NAICS Code						
– Investments	-0.007*	-0.008**	-0.006	-0.011**	-0.013***	-0.009
(N = 7,724)	(-1.84)	(-3.18)	(-1.24)	(-2.20)	(-3.18)	(-1.59)
– Return on Assets	-0.002	-0.014	0.004	-0.003	-0.019	0.004
(N = 7,724)	(-0.28)	(-1.26)	(0.46)	(-0.26)	(-1.28)	(0.34)

Table 11: Channels of the PGD-Investment Relation

This table reports the coefficients of OLS regressions investigating the channels behind the effects of PGD regulation on investments and return on assets (models (2) and (3)). The dependent variable in Panel A is the firm's quarterly capital expenditures divided by lagged book assets (*Investments*). The outcome variable in Panel B is the firm's operating income before depreciation divided by lagged book assets (*Return on Assets*). The key explanatory variable *PGD* is an indicator equal to one beginning in the quarter in which PGD regulation becomes effective for the given extractive company. *Direct-to-Consumer (Wholesale)* is a dummy variable equal to one if the extractive firm sells its products directly to end consumers (in wholesale markets). *PGD Published* is an indicator equal to one beginning in the quarter in which the firm publishes its first extraction payment report. All specifications include resource type-by-quarter fixed effects (where resource types are defined using the 3-digit NAICS code), firm fixed effects, and financial controls. The *between country* specifications additionally include country fixed effects and macroeconomic controls. In the *within country-year* models, I use country-by-quarter fixed effects (instead of country fixed effects and macro controls). T-statistics, reported in parentheses, are based on standard errors clustered at the level of the extractive company. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Investments / Total Assets$_{t-1}$

	Between Country			Within Country-Year		
	(1)	(2)	(3)	(4)	(5)	(6)
PGD * Direct-to-Consumer	-0.007**			-0.010***		
	(-2.34)			(-2.73)		
PGD * Wholesale	-0.003			-0.004		
	(-0.84)			(-0.95)		
PGD Published		-0.007**	-0.068***		-0.009**	-0.085***
		(-2.35)	(-3.22)		(-2.04)	(-4.42)
PGD		-0.004	-0.041***		-0.005	-0.038***
		(-1.17)	(-5.89)		(-1.10)	(-4.70)
Observations	8,096	8,036	1,542	8,048	7,997	1,517
Adjusted R-Squared	0.425	0.424	0.614	0.418	0.418	0.629
F-Test: ΔPGD Coefficients (p-value)	0.341	0.521	0.177	0.156	0.490	0.010
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	No	No	No
HQ Country FE	Yes	Yes	Yes	No	No	No
HQ Country × Quarter FE	No	No	No	Yes	Yes	Yes
Resource Type × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	CEM	Full	Full	CEM
Cluster Level	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	583	578	170	582	577	168

Panel B: Return on Assets

	Between Country			Within Country-Year		
	(1)	(2)	(3)	(4)	(5)	(6)
PGD * Direct-to-Consumer	-0.032***			-0.043***		
	(-3.69)			(-3.75)		
PGD * Wholesale	0.002			-0.001		
	(0.24)			(-0.11)		
PGD Published		0.005	-0.039**		0.006	-0.050**
		(0.62)	(-2.32)		(0.58)	(-2.56)
PGD		-0.005	0.015		-0.006	0.021
		(-0.64)	(0.63)		(-0.58)	(1.07)
Observations	8,096	8,036	1,542	8,048	7,997	1,517
Adjusted R-Squared	0.629	0.629	0.695	0.625	0.625	0.701
F-Test: ΔPGD Coefficients (p-value)	0.001	0.406	0.069	0.000	0.436	0.008
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	No	No	No
HQ Country FE	Yes	Yes	Yes	No	No	No
HQ Country × Quarter FE	No	No	No	Yes	Yes	Yes
Resource Type × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	CEM	Full	Full	CEM
Cluster Level	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	583	578	170	582	577	168

Table 12: Segment-Level Analysis

This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on foreign investments at the segment level. The dependent variable *Segment Investments* is defined as the yearly capital expenditures by a given extractive firm in a given host country, divided by the lagged total assets in that particular segment. The key explanatory variable *PGD* is an indicator equal to one beginning in the year in which PGD regulation becomes effective for the given extractive company/segment. *Large (Mid/Small)* is an indicator variable equal to one if the parent company's average total assets exceed (are below) their 66th percentile value. *Higher (Lower)* Corruption is a dummy variable equal to one if the Corruption Perceptions Index (CPI) of a given host country is higher (lower) than the median CPI in the given year. *Africa*, *Asia*, *Latin America*, and *Europe* are separate indicator variables which equal one if the host country is located on the given continent. All specifications include host country-by-year fixed effects, resource type-by-year fixed effects (where resource types are defined using the 3-digit NAICS code), segment fixed effects, as well as parent company controls. I collect geographic segment-level investments from *Worldscope*. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the parent company's headquarter country. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Segment Investments / Segment Assets$_{t-1}$				
	(1)	(2)	(3)	(4)	(5)
PGD	-0.042**	-0.066***			
	(-2.41)	(-3.57)			
PGD * Large			-0.066***		
			(-3.43)		
PGD * Mid/Small			-0.064		
			(-0.93)		
PGD * Higher Corruption				-0.068**	
				(-2.49)	
PGD * Lower Corruption				-0.064**	
				(-2.62)	
PGD * Africa					-0.158***
					(-7.71)
PGD * Asia					-0.084*
					(-1.80)
PGD * Latin America					0.046***
					(9.09)
PGD * Europe					0.027
					(0.58)
Observations	2,887	2,887	2,887	2,887	2,887
Adjusted R-Squared	0.445	0.456	0.455	0.455	0.455
F-Test: ΔPGD Coefficients (p-value)	-	-	0.973	0.918	-
Parent Controls	No	Yes	Yes	Yes	Yes
Host Country × Year FE	Yes	Yes	Yes	Yes	Yes
Resource Type × Year FE	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes
Cluster Level	HQ Country	HQ Country	HQ Country	HQ Country	HQ Country
Number of Clusters	40	40	40	40	40

Figure 1: Host Country Identification Strategy
This figure illustrates the identification strategy of my extractive payment regressions. I employ a generalized difference-in-differences design based on the staggered roll out of PGD regulation. Each of my 13 host countries covers payment data from European, US, Australian, Chinese, and other multinational extractive companies on a subsidiary - host country - year level. Given the staggered and quasi-exogenous implementation of PGD regulation, different foreign subsidiaries of European extractive companies get treated at different points in time. My dependent variable is either the normalized total payments or the normalized gap between payments made by firms and payments received by governments. I fix the host country, year, and natural resource that is extracted. I then compare the change in payments or payment gaps of subsidiaries whose parent companies become subject to PGD regulation before and after with that of subsidiaries whose parents are not (yet) affected by the disclosure regulation. For example, Statoil, the largest Norwegian oil and gas company, became subject to PGD regulation in 2014. For Shell the disclosure regulation only became effective in 2015. Chevron is never treated and forms part of the non-disclosing control group since the United States did not implement extraction payment disclosures.

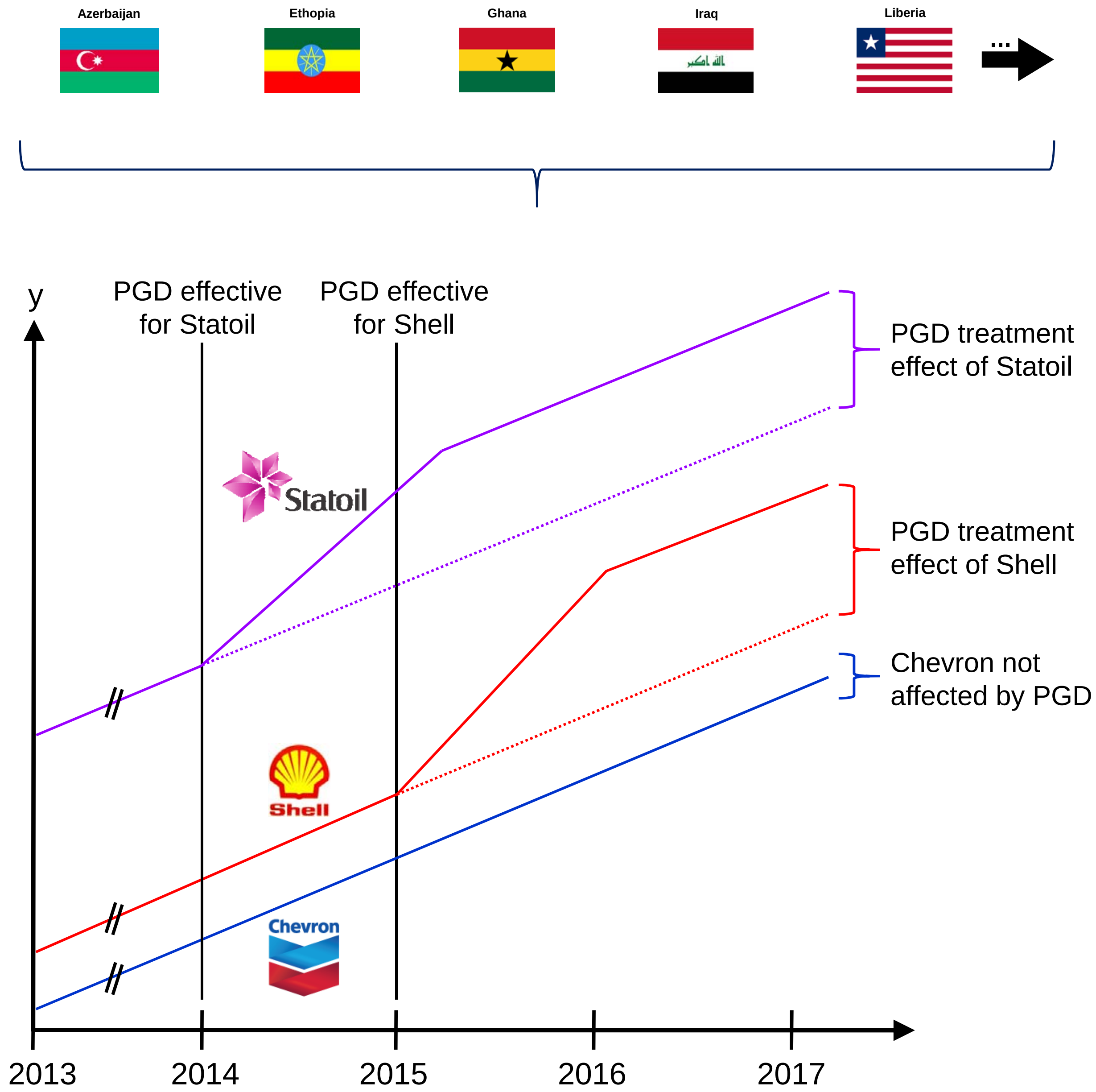


Figure 2: Extractive Payments in Event Time
This figure reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on payments to host governments in event time. I estimate model (1) but replace the *PGD* indicator variable with 4 separate dummies, each marking one time period relative to the entry-into-force year (t=0). I omit the indicator for year t-1, which serves as the benchmark period with an OLS coefficient and standard error of zero. Vertical bands represent 90% confidence intervals for the point estimates in each time period.

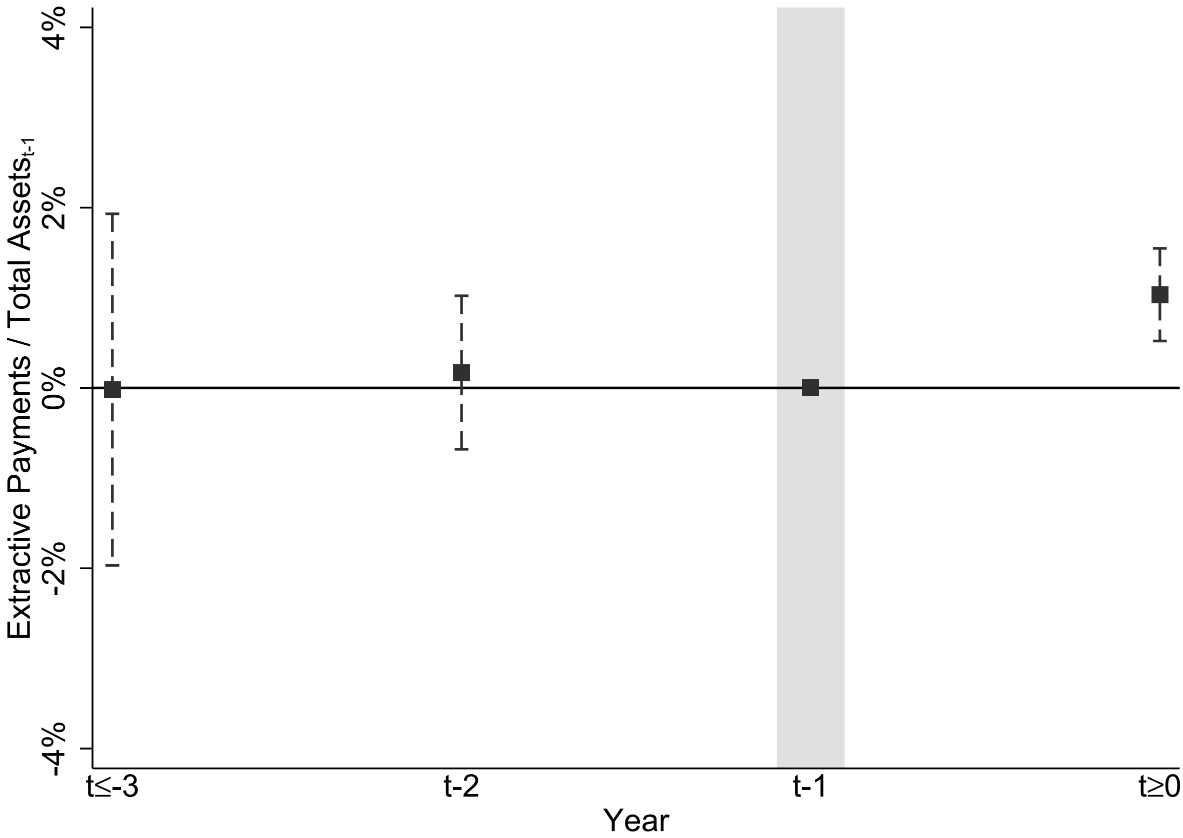
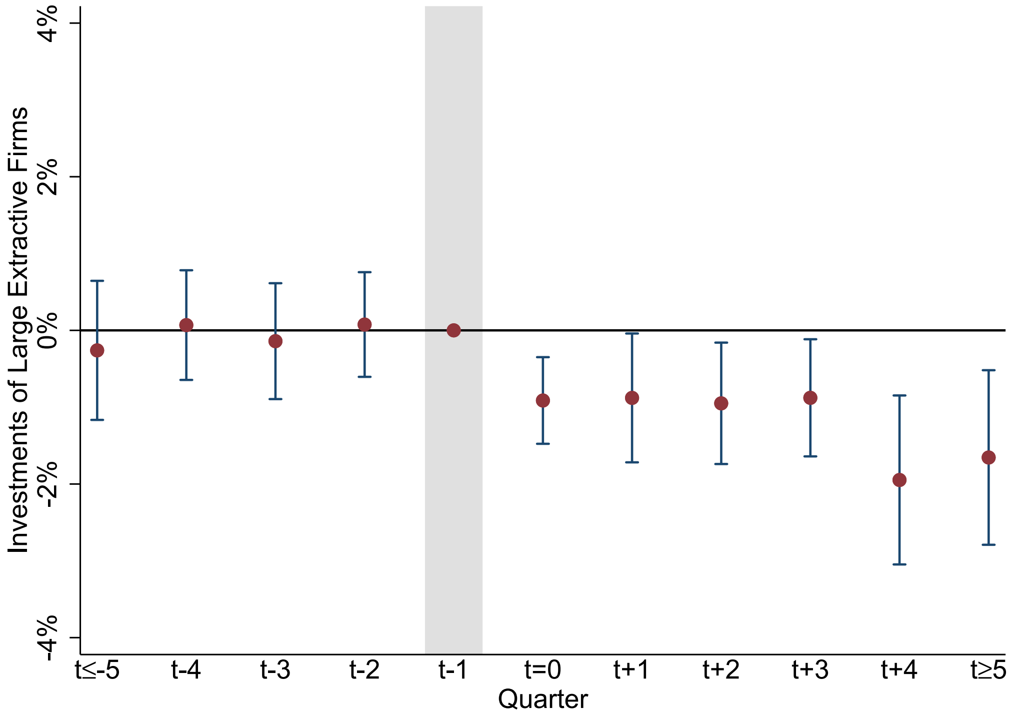


Figure 3: Investment Patterns of European Extractive Firms in Event Time
This figure reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on parent-level investments in event time. I estimate model (3) but replace the *PGD* indicator variable with 11 separate dummies, each marking one time period relative to the entry-into-force quarter (t=0). I omit the indicator for period t-1, which serves as the benchmark period with an OLS coefficient and standard error of zero. Vertical bands represent 90% confidence intervals for the point estimates in each time period. The upper (lower) panel plots the investment patterns for large (small/medium-sized) disclosing extractive companies. Firms are classified as large (small/medium-sized) if their average assets exceed (are below) the 66th percentile value.



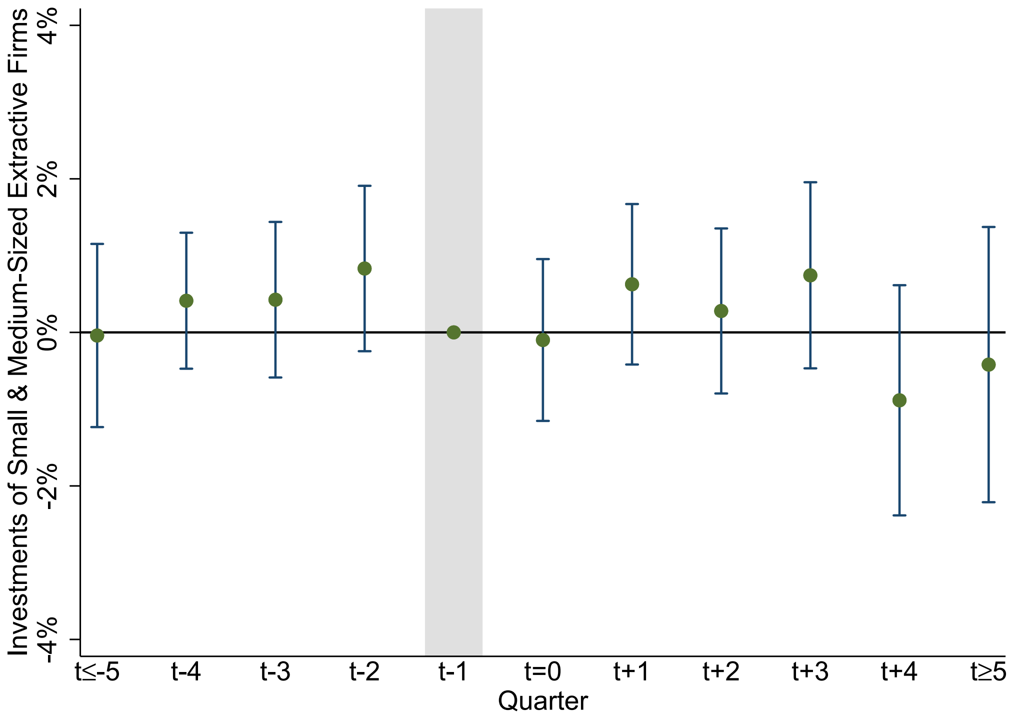


Figure 4: Investment Reallocation From Large Disclosing to Non-Disclosing Firms
This figure illustrates the reallocation of investments from large disclosing to non-disclosing firms once extraction payment disclosures become effective. I plot the average residualized capital expenditures from model (3) for both types of companies over time. For ease of exposition, I also normalize average investments by subtracting the mean and dividing by the standard deviation of each group. In order to compare average capital expenditures *within the same calendar quarter* across treatment and control groups, I focus on investment changes around the year 2015 since the majority of European extractive firms (roughly 60%) became subject to PGD regulation at the beginning of that year. My results are virtually identical if I compare investments in event time and use weighted averages to construct synthetic control groups for each quarter.

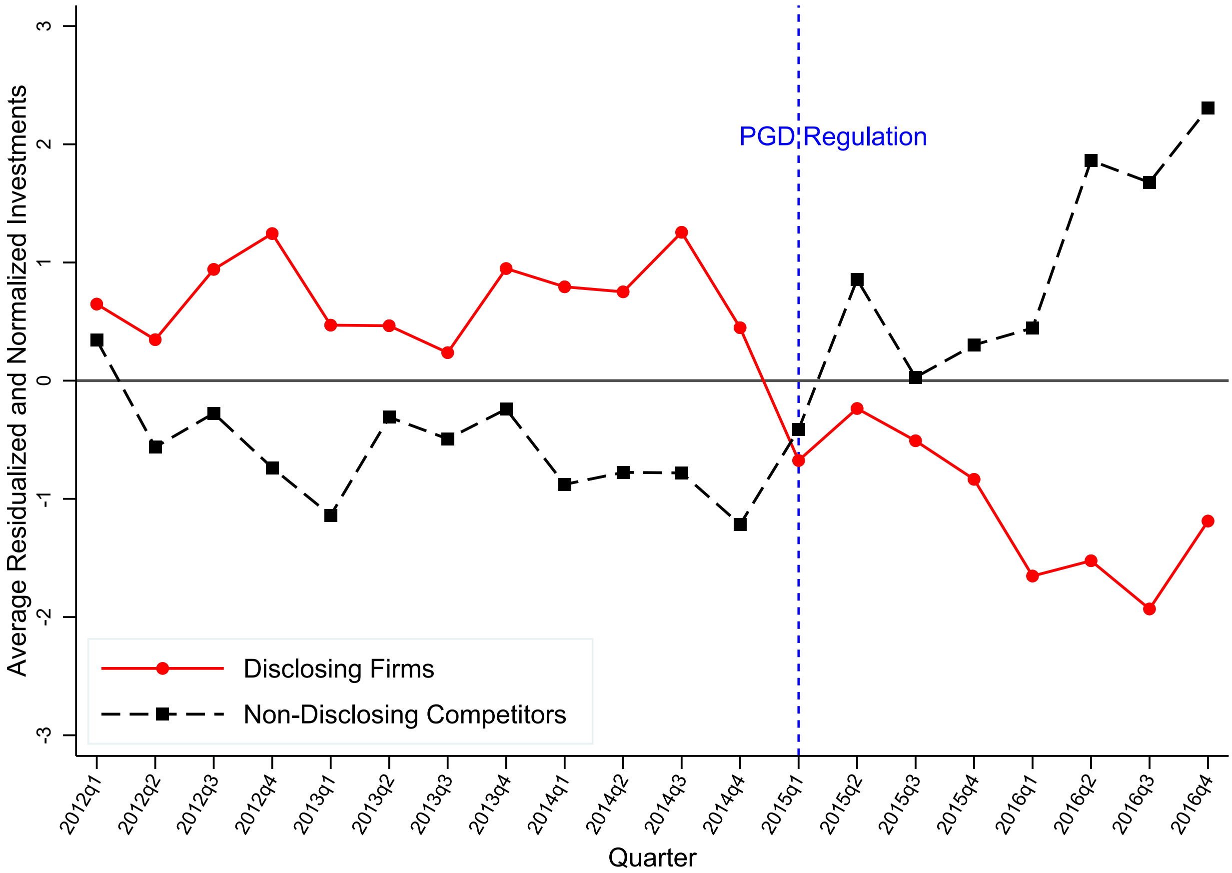
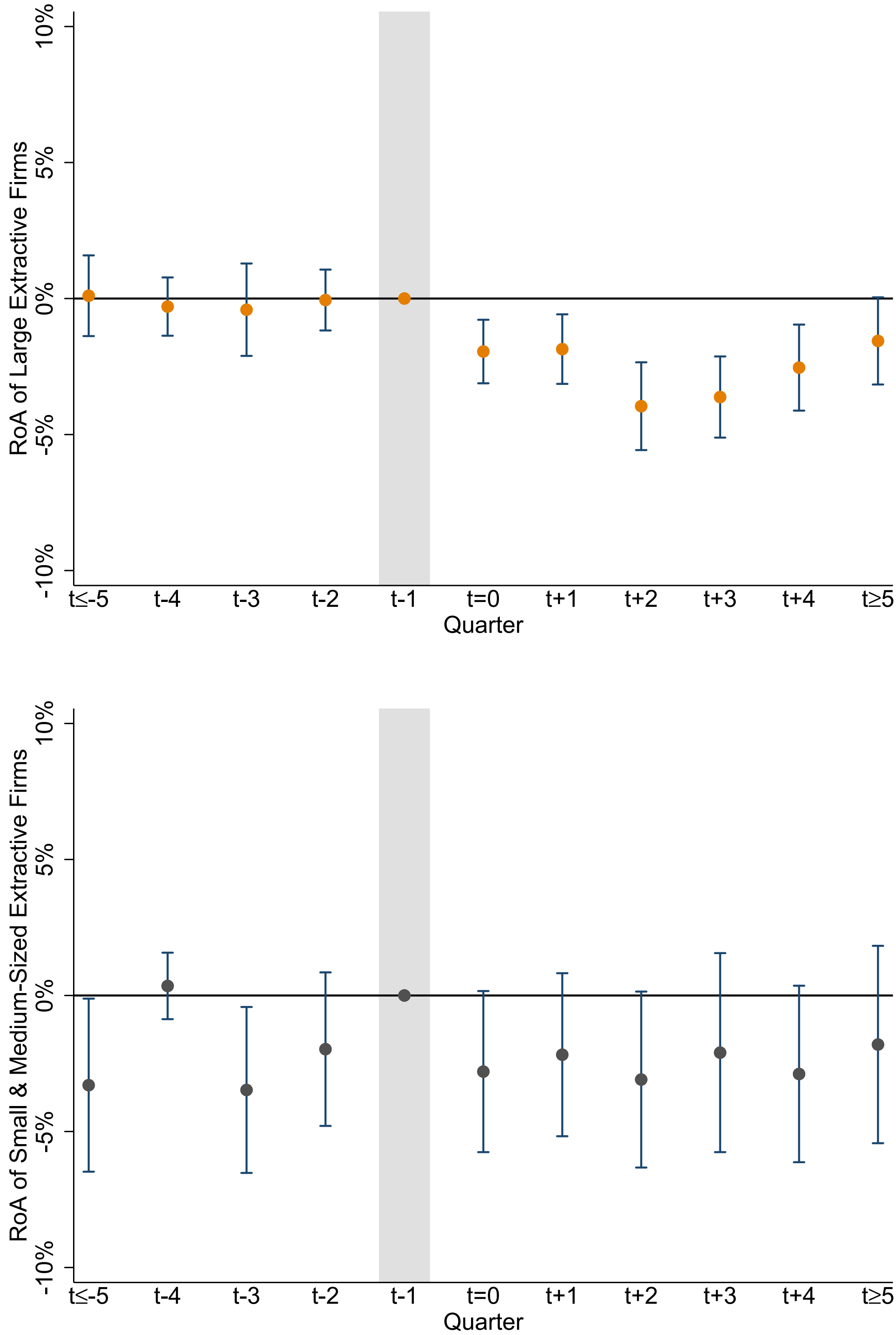


Figure 5: RoA Patterns of European Extractive Firms in Event Time
This figure reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on parent-level RoA in event time. I estimate model (3) but replace the *PGD* indicator variable with 11 separate dummies, each marking one time period relative to the entry-into-force quarter (t=0). I omit the indicator for period t-1, which serves as the benchmark period with an OLS coefficient and standard error of zero. Vertical bands represent 90% confidence intervals for the point estimates in each time period. The upper (lower) panel plots the investment patterns for large (small/medium-sized) disclosing extractive companies. Firms are classified as large (small/medium-sized) if their average assets exceed (are below) the 66th percentile value.



Appendix

Table A1: Variable Definitions
This table defines all variables used in the empirical analyses and indicates their data source.

Variable	Definition	Data Source
$\text{PGD}_{\text{i,t}}$	Indicator variable equal to one beginning in the period t in which PGD regulation becomes effective for extractive company i, zero otherwise.	EU Commission, federal law gazettes, investor relations webpages
$\text{Extractive Payment}_{\text{i,hc,t}}$	Total payments by extractive company i to host government hc in year t.	EITI Reports
$\text{Payment Gap}_{\text{i,hc,t}}$	Difference between payments made by extractive company i and payments officially received by host government hc in year t.	EITI reports
$\text{Investments}_{\text{i,t}}$	Capital expenditures of company i in period t.	Compustat
$\text{Segment Investments}_{\text{i,hc,t}}$	Capital expenditures of company i in host country hc and period t.	Worldscope
$\text{Return on Assets}_{\text{i,t}}$	Operating income before depreciation of company i in period t divided by lagged book assets.	Compustat
$\text{Total Assets}_{\text{i,t}}$	Total book assets of company i in period t.	Compustat
$\text{PPE}_{\text{i,t}}$	Plant, property, and equipment of company i in period t divided by total book assets.	Compustat
$\text{Leverage}_{\text{i,t}}$	Long-term debt plus debt in current liabilities of company i in period t divided by total assets.	Compustat
$\text{Q}_{\text{i,t}}$	Market value of assets of company i in period t divided by book value of assets. Market value of assets equals the book value of assets plus the market value of equity minus the book value of equity.	Compustat
$\text{Asset Turnover}_{\text{i,t}}$	Sales of company i in period t divided by total book assets.	Compustat
$\text{Cash}_{\text{i,t}}$	Cash and short-term investments of company i in period t divided by total assets.	Compustat
Large_{i}	Indicator variable equal to one if the average total assets of extractive company i exceed the 66th percentile value, zero otherwise.	Compustat
$\text{Mid/Small}_{\text{i}}$	Indicator variable equal to one if the average total assets of extractive company i are below the 66th percentile value, zero otherwise.	Compustat

Higher Corruption$_{hc,t}$	Indicator variable equal to one if the Corruption Perceptions Index (CPI) of host country hc is higher than the median CPI in a given year t, zero otherwise.	EITI Reports, Transparency International
Lower Corruption$_{hc,t}$	Indicator variable equal to one if the Corruption Perceptions Index (CPI) of host country hc is lower than the median CPI in a given year t, zero otherwise.	EITI Reports, Transparency International
Direct-to-Consumer$_{i}$	Indicator variable equal to one if extractive firm i sells its products directly to end consumers, zero otherwise.	Annual filings
Wholesale $_{i}$	Indicator variable equal to one if extractive firm i sells its products in wholesale markets, zero otherwise.	Annual filings
PGD Published $_{i,t}$	Indicator variable equal to one beginning in the quarter in which the firm publishes its first extraction payment report, zero otherwise.	Investor relations webpages
Implementation Time PGD$_{c}$	Number of months it took country c to transpose PGD regulation into national law.	European Commission
Average Transposition Delay$_{c}$	Average implementation delay of European country c across all previous directives.	Eurostat
Southern Country$_{c}$	Indicator variable equal to one for Portugal, Spain, Italy, and Greece, zero otherwise.	Christensen et al. (2016)
Country Size$_{c}$	Population of European country c at the end of 2012 in millions.	Christensen et al. (2016)
Implementation Time TPD$_{c}$	Number of months it took country c to transpose the Transparency Directive into national law.	Christensen et al. (2016)
Implementation Time MAD$_{c}$	Number of months it took country c to transpose the Market Abuse Directive into national law.	Christensen et al. (2016)
Imp. of Extractive Sector$_{c}$	Market value of all extractive firms in European country c divided by the country's total stock market capitalization.	Compustat
Corruption$_{hc,t}$	100 - Corruption Perceptions Index of host country hc in year t.	Transparency International
Oil Output$_{hc,t}$	Oil production of host country hc in year t in ktoe.	World Bank
Tot. Pmt. / GDP$_{hc,t}$	Total extractive payments of host country hc in year t divided by the national GDP and multiplied by 100.	World Bank
Voice$_{hc,t}$	Survey measure capturing the extent to which a host country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media in year t.	World Bank

Regulatory Quality$_{hc,t}$	Survey measure capturing the host government's ability to formulate and implement sound policies and regulations that permit and promote private sector development in year t.	World Bank
Government Exp.$_{hc,t}$	Host government's total consumption expenditures in year t divided by the national GDP and multiplied by 100.	World Bank
Military Exp.$_{hc,t}$	Host government's military expenditures in year t divided by the national GDP and multiplied by 100.	World Bank
Education Exp.$_{hc,t}$	Host government's education expenditures in year t divided by the national GDP and multiplied by 100.	World Bank
Health Exp.$_{hc,t}$	Host government's health expenditures in year t divided by the national GDP and multiplied by 100.	World Bank
Total Payments$_{hc,t}$	Total extractive payments to host country hc in year t.	EITI Reports
Discl. / Total Pmt.$_{hc,t}$	Fraction of extractive revenues that are subject to PGD regulation in host country hc divided by the country's total extractive revenues and multiplied by 100.	EU Commission, federal law gazettes, EITI Reports
GDP$_{hc,t}$	Real gross domestic product of host country hc in year t in USD bn.	World Bank
PGD[0]$_{i,t}$	Indicator variable equal to one on the publication day of the extraction payment report, zero otherwise.	LSE Regulatory News Service
PGD[0;n]$_{i,t}$	Indicator variable equal to one on the publication day of the extraction payment report and n days thereafter, zero otherwise.	LSE Regulatory News Service
PGD$_{i,t}$	Indicator variable equal to one beginning at the publication date of the extraction payment report.	LSE Regulatory News Service
Bid-Ask Spread$_{i,t}$	Relative equity bid-ask spread calculated as (Ask - Bid) / ((Ask + Bid) * 0.5).	Datastream
Stock Return$_{i,t}$	Ln(return index$_{t}$) - ln(return index$_{t-1}$).	Datastream
Market Value$_{i,t}$	Stock price times outstanding shares.	Datastream
Share Turnover$_{i,t}$	Trading volume divided by number of outstanding shares.	Datastream
Return Variability$_{i,t}$	Weekly rolling standard deviation of Stock Return.	Datastream

Internet Appendix to

Disclosure Regulation, Corruption, and Investment: Evidence from Natural Resource Extraction

Thomas Rauter

Table of Contents

Internet Appendix A: Exogeneity of PGD Implementation Timing

Table IA1: Country-Level Determinants of PGD Adoption Timing
This table reports the coefficients of OLS regressions assessing the exogeneity of PGD's implementation timing across Europe. Each observation corresponds to one European country. *Implementation Time PGD* captures the implementation time in months from the enactment of PGD regulation at the EU level (23-Jun-2013) to its entry-into-force date in each country (see Table 1). *Average Transposition Delay* is the country's average implementation delay across all previous European directives. *Southern Country* is an indicator variable equal to one for Italy, Spain, Portugal, and Greece. *Country Size* is the country's population in millions. *Importance of Extractive Sector* is defined as the market value of all extractive companies listed in that country divided by the total market capitalization of the country's stock market. *Implementation Time TPD (MAD)* is the time in months from the enactment of the Transparency Directive (Market Abuse Directive) at the EU level to its entry-into-force date in each country. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Implementation Time PGD (months)			
	(1)	(2)	(3)	(4)
Average Transposition Delay	0.462	0.606**	0.530*	0.615**
	(1.65)	(2.24)	(1.84)	(2.20)
Southern Country	5.976*	5.902**	5.603*	5.815*
	(2.07)	(2.20)	(1.92)	(2.09)
Country Size	-0.067	-0.084*	-0.069	-0.083
	(-1.32)	(-1.76)	(-1.37)	(-1.71)
Importance of Extractive Sector	-0.103	-0.130	-0.130	-0.135
	(-1.22)	(-1.64)	(-1.47)	(-1.60)
Implementation Time TPD		0.254*		0.240
		(2.04)		(1.71)
Implementation Time MAD			0.215	0.053
			(1.00)	(0.23)
Observations	25	25	25	25
Adjusted R-Squared	0.145	0.262	0.144	0.223

Internet Appendix B: Aggregate Effects of Extraction Payment Disclosures

Table IA2: Aggregate Effects of PGD Regulation in Foreign Host Countries
This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on aggregate host country corruption, governance, oil output, and government spending (model (4)). *Corruption* is defined as 100 minus the Corruption Perceptions Index by Transparency International. *Voice* is the World Bank's governance indicator reflecting the extent to which a country's citizens are able to participate in selecting their government. *Regulatory Quality* is the World Bank's survey measure reflecting the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. *Oil Output* is the natural logarithm of a country's yearly oil production in ktoe. *Government Expenditures* is the host government's consumption expenditure as a percent of GDP. *Military Expenditures*, *Education Expenditures*, and *Health Expenditures* are defined as the country's military, education, and health expenditures divided by GDP. *Disclosed Payments / Total Payments* is the fraction of a country's total extractive revenues that is disclosed in PGD reports by oil, gas, or mining firms. *Total Payments / GDP* is defined as the ratio of a host country's total extractive revenues divided by GDP. *Ln(GDP)* is the natural logarithm of the country's GDP. All specifications include host country and year fixed effects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the host country. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Corruption	Voice	Oil Output	Regulatory Quality	Government Expenditures	Military Expenditures	Education Expenditures	Health Expenditures
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disclosed Payments / Total Payments	0.028	-0.002	-0.007	0.003***	-0.018	-0.010	1.278***	0.005
	(1.16)	(-1.49)	(-1.62)	(3.91)	(-1.35)	(-0.84)	(3.14)	(0.57)
Total Payments / GDP	-0.090	-0.002	-0.008	0.002**	-0.078***	-0.019	-0.008	0.000
	(-1.26)	(-1.09)	(-0.99)	(2.55)	(-3.22)	(-1.59)	(-1.60)	(0.07)
Ln(GDP)	-7.129*	-0.137	-0.142	0.011	-0.222	-0.324	-2.496	0.879
	(-1.87)	(-0.99)	(-0.23)	(0.09)	(-0.10)	(-0.73)	(-1.22)	(0.64)
Observations	137	123	109	123	146	138	80	143
Adjusted R-Squared	0.980	0.990	0.974	0.991	0.962	0.894	0.814	0.911
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host Country Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	(Host) Country	Country	Country	Country	Country	Country	Country	Country
Number of Clusters	36	32	27	32	38	37	23	38

Internet Appendix C: Coarsened Exact Matching

Table IA3: Covariate Imbalance pre/post Coarsened Exact Matching
This table reports covariate imbalances before and after coarsened exact matching (CEM) for the variables used in my payment, investment, and RoA regressions (Iacus et al. (2012)). The $\mathcal{L}_1$ distance measures the covariate imbalance between disclosing and non-disclosing firms based on financial characteristics before the adoption of extraction payment disclosures. $\mathcal{L}_1$ is bounded between zero and one and a lower value indicates a lower imbalance. I also report differences in the mean, minimum, 25% quantile (p25), median (p50), 75% quantile (p75), and maximum across treatment and control groups.

Panel A: Payment Regressions

	$\mathcal{L}_1$ Distance	ΔMean	ΔMin	Δp25	Δp50	Δp75	ΔMax
Before CEM: Multivariate $\mathcal{L}_1$ Distance = 0.822							
Ln(Total Assets$_{\text{pre-PGD}}$)	0.615	6.674	0.000	8.929	11.414	4.196	-0.787
Return on Assets$_{\text{pre-PGD}}$	0.648	0.086	0.000	0.097	0.122	0.102	-0.047
After CEM: Multivariate $\mathcal{L}_1$ Distance = 0.245							
Ln(Total Assets$_{\text{pre-PGD}}$)	0.045	0.021	0.000	0.207	0.155	0.218	0.083
Return on Assets$_{\text{pre-PGD}}$	0.169	0.002	0.000	0.012	0.004	0.019	-0.015

Panel B: Investment and RoA Regressions

	$\mathcal{L}_1$ Distance	ΔMean	ΔMin	Δp25	Δp50	Δp75	ΔMax
Before CEM: Multivariate $\mathcal{L}_1$ Distance = 0.891							
Ln(Total Assets$_{\text{pre-PGD}}$)	0.478	3.170	0.000	4.700	4.247	2.407	0.030
Asset Turnover$_{\text{pre-PGD}}$	0.396	0.033	0.000	0.000	0.081	0.044	-0.359
PPE$_{\text{pre-PGD}}$	0.440	0.069	0.000	0.311	0.127	-0.133	-0.162
Cash$_{\text{pre-PGD}}$	0.376	-0.008	0.000	0.026	0.046	0.010	-0.621
Leverage$_{\text{pre-PGD}}$	0.295	-0.059	0.000	0.000	0.121	-0.028	-6.113
Q$_{\text{pre-PGD}}$	0.208	-1.629	0.000	0.561	-0.240	-0.552	-164.127
After CEM: Multivariate $\mathcal{L}_1$ Distance = 0.460							
Ln(Total Assets$_{\text{pre-PGD}}$)	0.409	0.180	0.000	0.000	0.000	0.437	0.751
Asset Turnover$_{\text{pre-PGD}}$	0.251	-0.001	0.000	0.000	0.000	-0.008	0.020
PPE$_{\text{pre-PGD}}$	0.018	-0.005	0.000	0.000	0.000	-0.023	-0.002
Cash$_{\text{pre-PGD}}$	0.316	-0.003	0.000	0.000	0.000	-0.003	-0.020
Leverage$_{\text{pre-PGD}}$	0.268	-0.005	0.000	0.000	0.000	-0.068	-0.023
Q$_{\text{pre-PGD}}$	0.434	-0.384	0.000	0.000	0.000	-1.540	-8.333

Internet Appendix D: Additional Descriptive Statistics

Table IA4: Variables Used in Aggregate Host Country Regressions
This table reports descriptive statistics for the variables used in my aggregate host country analyses. I report the number of observations (N), mean, standard deviation (SD), 10% quantile (p10), 25% quantile (p25), median (p50), 75% quantile (p75), and 90% quantile (p90). I define all variables in Table A1. I obtain the corruption index from *Transparency International* and payment data from the *Extractive Industries Transparency Initiative (EITI).* I retrieve all remaining macroeconomic variables from the open data library of the *World Bank.* This sample covers host countries during the time period 2010 to 2015.

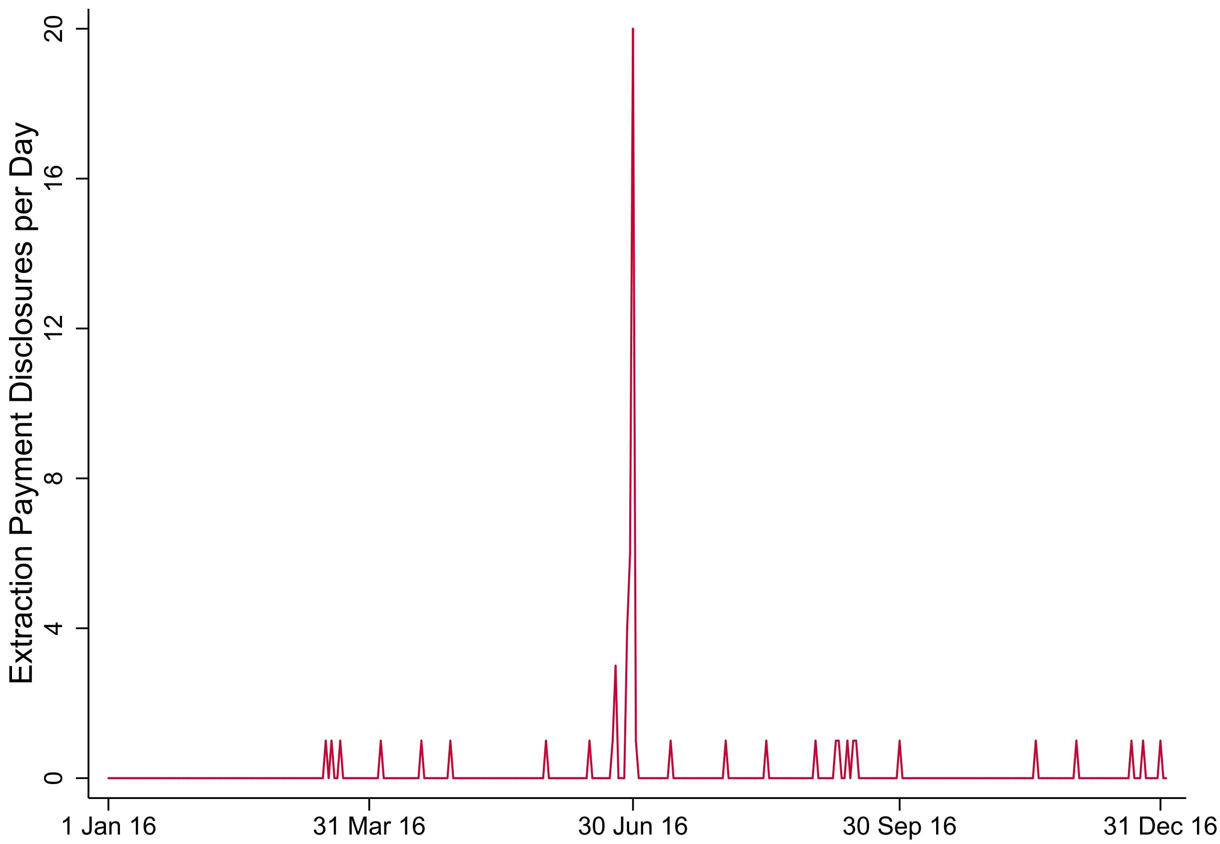
	N	Mean	Std. Dev.	p10	p25	p50	p75	p90
Corruption	144	67.018	15.162	57.000	63.000	70.068	75.492	79.595
Voice	129	-0.341	0.745	-1.250	-0.984	-0.291	0.032	0.459
Oil Output	114	27.684	53.020	0.000	0.094	2.095	40.929	83.756
Regulatory Quality	129	-0.324	0.677	-1.055	-0.771	-0.390	-0.129	0.407
Government Expenditures	152	16.076	12.020	9.518	10.826	13.472	18.122	21.000
Military Expenditures	145	1.737	1.275	0.654	0.927	1.347	1.872	3.399
Education Expenditures	93	4.318	1.911	2.462	2.851	3.733	5.751	7.193
Health Expenditures	151	5.594	2.353	3.318	4.236	5.232	6.329	9.157
Disclosed Payments / Total Payments (×100)	158	1.189	5.855	0.000	0.000	0.000	0.000	0.000
$1_{\text{Disclosed Payments}>0}$	158	0.076	0.266	0.000	0.000	0.000	0.000	0.000
Total Payments / GDP (×100)	158	13.787	41.136	0.412	1.074	4.456	11.173	20.740
Ln(GDP)	158	23.845	1.936	21.389	22.696	23.710	24.694	26.634

Table IA5: Variables Used in Capital Market Analyses
This table reports descriptive statistics for the variables used in my capital market analyses. I report the number of observations (N), mean, standard deviation (SD), 10% quantile (p10), 25% quantile (p25), median (p50), 75% quantile (p75), and 90% quantile (p90). I define all variables in Table A1. I obtain stock market variables from *Datastream* and PGD publication dates from the extraction payment disclosures of the respective companies. This sample covers London Stock Exchange listed extractive firms during 2016.

	N	Mean	Std. Dev.	p10	p25	p50	p75	p90
Bid-Ask Spread	8616	0.036	0.093	0.001	0.001	0.007	0.034	0.098
Stock Return	8616	0.001	0.025	-0.029	-0.012	0.000	0.014	0.032
PGD[0]	8616	0.003	0.055	0.000	0.000	0.000	0.000	0.000
PGD[0,1]	8616	0.006	0.077	0.000	0.000	0.000	0.000	0.000
PGD[0,2]	8616	0.008	0.092	0.000	0.000	0.000	0.000	0.000
PGD[0,3]	8616	0.011	0.103	0.000	0.000	0.000	0.000	0.000
PGD[0,4]	8616	0.013	0.114	0.000	0.000	0.000	0.000	0.000
PGD	8616	0.353	0.478	0.000	0.000	0.000	1.000	1.000
Market Value$_{t-5}$	8616	11.411	24.328	0.029	0.190	1.693	7.502	38.946
Share Turnover$_{t-5}$	8616	0.003	0.007	0.000	0.000	0.001	0.003	0.006
Return Variability$_{t-5}$	8616	0.028	0.038	0.008	0.013	0.021	0.034	0.054

Internet Appendix E: Publication Dates of PGD Reports

Figure IA1: Publication Dates of UK Extraction Payment Disclosures during 2016
This figure illustrates the publication timing of the first PGD reports by London Stock Exchange listed extractive companies during 2016. The horizontal axis captures the year 2016. The vertical axis depicts the number of published extraction payment reports per day.



Internet Appendix F: Capital Market Effects of Extraction Payment Disclosures

Table IA6: Market Liquidity Around Extraction Payment Disclosure Dates

This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on stock market liquidity (model (5)). The dependent variable *Ln(Bid-Ask Spread)* is the natural logarithm of the daily, relative bid ask-spread calculated as (Ask - Bid) / ((Ask + Bid) * 0.5). *PGD[0(;n)]* is an indicator which equals one at the publication date of the extraction payment report (and n trading days thereafter). *PGD* is a dummy variable equal to one beginning at the publication date of the extraction payment report. *Ln(Market Value)*$_{t-5}$ is the natural logarithm of the firm's daily market capitalization lagged by one trading week. *Ln(Share Turnover)*$_{t-5}$ is the natural logarithm of the daily trading volume divided by the number of outstanding shares multiplied by 100 and lagged by one trading week. *Ln(Return Variability)*$_{t-5}$ is the natural logarithm of the stock return's 5-day rolling standard deviation, lagged by one trading week. All specifications include trading day and firm fixed effects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the firm and trading day. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Ln(Bid-Ask Spread)											
	Full Sample						*Without End of June Disclosures*					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PGD[0]	-0.059						-0.176*					
	(-0.84)						(-1.96)					
PGD[0,1]		-0.031						-0.110*				
		(-0.52)						(-1.73)				
PGD[0,2]			-0.079						-0.187**			
			(-1.25)						(-2.62)			
PGD[0,3]				-0.093						-0.153**		
				(-1.67)						(-2.27)		
PGD[0,4]					-0.059						-0.135*	
					(-0.95)						(-1.96)	
PGD						0.014						0.030
						(0.20)						(0.27)
Ln(Market Value)$_{t-5}$	-0.613***	-0.613***	-0.613***	-0.613***	-0.613***	-0.613***	-0.557***	-0.557***	-0.557***	-0.557***	-0.557***	-0.556***
	(-3.83)	(-3.83)	(-3.83)	(-3.83)	(-3.83)	(-3.80)	(-2.80)	(-2.80)	(-2.80)	(-2.80)	(-2.80)	(-2.85)
Ln(Share Turnover)$_{t-5}$	-0.038**	-0.038**	-0.038**	-0.038**	-0.038**	-0.038**	-0.043*	-0.044*	-0.044*	-0.044*	-0.044*	-0.043*
	(-2.18)	(-2.19)	(-2.19)	(-2.19)	(-2.19)	(-2.15)	(-1.79)	(-1.80)	(-1.80)	(-1.81)	(-1.82)	(-1.80)
Ln(Return Variability)$_{t-5}$	0.048**	0.048**	0.049**	0.049**	0.049**	0.048**	0.048**	0.049**	0.049**	0.049**	0.049**	0.048**
	(2.57)	(2.58)	(2.57)	(2.57)	(2.58)	(2.56)	(2.04)	(2.04)	(2.02)	(2.04)	(2.04)	(2.06)
Observations	8,929	8,929	8,929	8,929	8,929	8,929	5,675	5,675	5,675	5,675	5,675	5,675
Adjusted R-Squared	0.943	0.943	0.943	0.943	0.943	0.943	0.954	0.954	0.954	0.954	0.954	0.954
Day Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day
Number of Firm Clusters	74	74	74	74	74	74	50	50	50	50	50	50
Number of Day Clusters	250	250	250	250	250	250	249	249	249	249	249	249

Table IA7: Stock Returns Around Extraction Payment Disclosure Dates

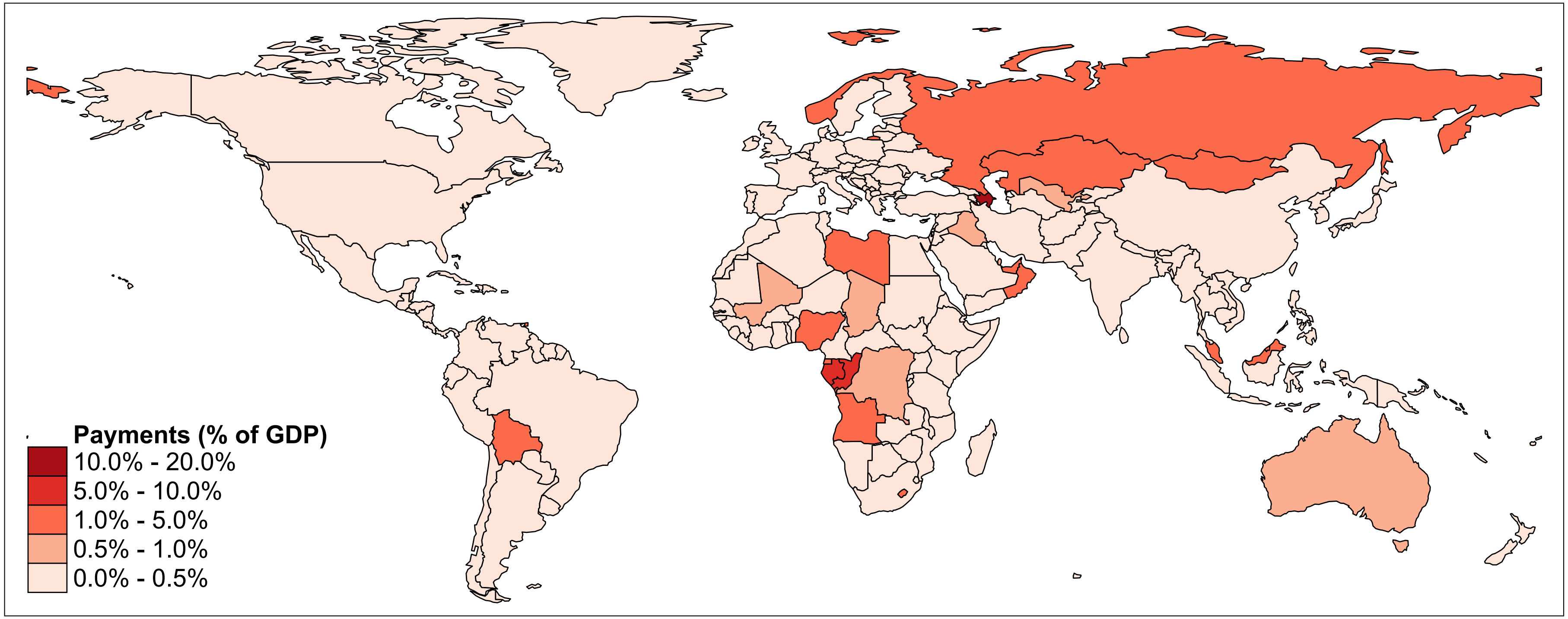
This table reports the coefficients of OLS regressions investigating the effect of extraction payment disclosures on stock returns (model (5)). The dependent variable *Ln(Stock Return)* is the natural logarithm of the daily stock return, calculated as $\ln(\text{return index}_t) - \ln(\text{return index}_{t\text{-}1})$. *PGD[0(;n)]* is an indicator which equals one at the publication date of the extraction payment report (and n trading days thereafter). *PGD* is a dummy variable equal to one beginning at the publication date of the extraction payment report. *Ln(Market Value)*$_{t-5}$ is the natural logarithm of the firm's daily market capitalization lagged by one trading week. *Ln(Share Turnover)*$_{t-5}$ is the natural logarithm of the daily trading volume divided by the number of outstanding shares multiplied by 100 and lagged by one trading week. *Ln(Return Variability)*$_{t-5}$ is the natural logarithm of the stock return's 5-day rolling standard deviation, lagged by one trading week. All specifications include trading day and firm fixed effects. T-statistics, reported in parentheses, are based on standard errors clustered at the level of the firm and trading day. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Stock Return (%)											
	Full Sample						*Without End of June Disclosures*					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PGD[0]	0.038						-0.484					
	(0.08)						(-0.71)					
PGD[0,1]		0.390						-0.430				
		(0.78)						(-0.95)				
PGD[0,2]			0.087						-0.490			
			(0.19)						(-1.46)			
PGD[0,3]				0.060						-0.458		
				(0.15)						(-1.45)		
PGD[0,4]					0.240						-0.324	
					(0.78)						(-1.56)	
PGD						0.013						-0.035
						(0.12)						(-0.21)
Ln(Market Value)$_{t-5}$	-0.625***	-0.626***	-0.625***	-0.625***	-0.626***	-0.626***	-0.626***	-0.625***	-0.626***	-0.626***	-0.626***	-0.629***
	(-4.70)	(-4.71)	(-4.70)	(-4.71)	(-4.70)	(-4.75)	(-4.61)	(-4.61)	(-4.62)	(-4.62)	(-4.62)	(-4.56)
Ln(Share Turnover)$_{t-5}$	0.027	0.027	0.027	0.027	0.027	0.027	0.003	0.003	0.003	0.002	0.002	0.003
	(1.30)	(1.31)	(1.30)	(1.30)	(1.31)	(1.29)	(0.22)	(0.17)	(0.17)	(0.15)	(0.14)	(0.21)
Ln(Return Variability)$_{t-5}$	0.056	0.056	0.056	0.056	0.056	0.056	0.078	0.078	0.078	0.079	0.079	0.077
	(1.11)	(1.10)	(1.10)	(1.11)	(1.09)	(1.10)	(1.36)	(1.37)	(1.37)	(1.38)	(1.38)	(1.36)
Observations	8,615	8,615	8,615	8,615	8,615	8,615	5,423	5,423	5,423	5,423	5,423	5,423
Adjusted R-Squared	0.146	0.146	0.146	0.146	0.146	0.146	0.150	0.150	0.150	0.150	0.150	0.150
Day Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day
Number of Firm Clusters	74	74	74	74	74	74	50	50	50	50	50	50
Number of Day Clusters	250	250	250	250	250	250	249	249	249	249	249	249

Internet Appendix G: Geographical Distribution of Extractive Payments

Figure IA2: Payments to Host Governments by UK listed Extractive Companies in 2015

This figure shows the geographical distribution of payments to host governments by London Stock Exchange listed (Main Market) extractive issuers in 2015. Darker shades of red correspond to higher total extractive payments as a percentage of the country's GDP. This figure covers payments by UK listed oil, gas, and mining companies during 2015.



Procyclicality of U.S. Bank Leverage

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May 2018

Abstract

In light of the current debate about the link between accounting and financial stability, we investigate the determinants of procyclical book leverage for US commercial and savings banks. We find that total asset growth and GDP growth are both positively related to book leverage growth. Our evidence is not consistent with the notion that fair value accounting contributes to procyclical leverage or that historical cost accounting reduces procyclicality. Overall, the business model of banks is more important for procyclical leverage than accounting or regulatory risk weights.

JEL-Classification: E32; G20; G28; G32; M41

Keywords: Banks; Fair Value Accounting; Financial Crisis; Leverage; Procyclicality; Risk-Based Capital Regulation

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We thank an anonymous referee for valuable comments that have greatly helped to improve the paper. We also thank Tobias Berg, Jannis Bischof, José García-Montalvo, Alois Geyer, Joseph Haubrich, Christian Leuz, Florian Nagler, Stephen Ryan, Markus Schmidt, Nikola Tarashev, and seminar participants at Goethe University Frankfurt, Vienna University of Economics and Business, the 2016 Journal of Accounting Research Conference (Chicago), the 2016 Deutsche Bundesbank-SAFE-ZEW-CEPR Joint Conference on Regulating Financial Markets (Frankfurt), the 2015 ÖFG Workshop on Accounting, Information, and Financial Crises (Graz), the 2015 European Accounting Association Meeting (Glasgow), the 2014 European Finance Association Meeting (Lugano), the 2014 Barcelona Summer Forum, as well as the 2014 Basel Committee and Deutsche Bundesbank Joint Conference (Eltville) for helpful comments and suggestions. Stanka Mauerová provided excellent research assistance.

1 Introduction

We investigate the role of accounting and regulation for procyclical book leverage of US commercial and savings banks.[1] Understanding these determinants is important for financial reporting, regulation, and bank management, especially in light of the recent debate about fair value accounting and its contribution to financial (in)stability. We are particularly interested in available for sale (AfS) securities, which is by far the largest and for many banks the only security class that is recognized at fair value.

The financial crisis of 2007-2009 triggered a vigorous debate about the role of fair value accounting and revived discussions about procyclicality in banking. While there is ample evidence that fair value accounting did not play a major role during the crisis, there is still the concern that fair value accounting contributes to instability by inflating credit bubbles via procyclical leverage.[2]

By originating loans and holding debt securities, banks play an important role in the provision of credit to the economy. Expansions and contractions of bank balance sheets and the amount of debt that banks use to fund their assets are important for access to credit. It is broadly recognized that banks' ability to borrow against collateral depends on the margin requirement and value of the asset, which can give rise to procyclicality and detrimental effects in financial intermediation (e.g., Geanakoplos (2003), Fostel and Geanakoplos (2008), Brunnermeier and Pedersen (2009), and Gorton and Metrick (2012)). Banks also face implicit margin requirements when using debt to finance a portfolio of

[1] We refer to "procyclical book leverage" as "procyclical (bank) leverage", "leverage procyclicality", or "procyclicality".

[2] See, e.g., Benston (2008), Ryan (2008), Securities and Exchange Commission (2008), Laux and Leuz (2009, 2010), Barth and Landsman (2010), Bhat et al. (2011), Badertscher et al. (2012), and Huizinga and Laeven (2012) for the debate about the role of fair value accounting during the financial crisis including empirical evidence. For a discussion about the significance and origin of procyclical bank leverage, see, for example, Persaud (2008), Plantin et al. (2008), International Monetary Fund (2008), Bank for International Settlements (2009), and Financial Services Authority (2009).

assets on their balance sheet (Adrian and Shin (2014)). Therefore, bank balance sheets can be subject to similar procyclicality as securities lending (collateralization).

Adrian and Shin (2010, 2014) measure procyclical bank leverage as a positive association between changes in book leverage and changes in total book assets. Book leverage is defined as total book assets over book equity. This approach is used in several articles (see, for example, Damar et al. (2013) and Beccalli et al. (2015)), and regulators as well as the business press often refer to it when arguing that fair value accounting contributes to procyclical leverage (e.g., Panetta and Angelini (2009), Economist (2008), and Financial Times (2008)). The concern is that if banks recognize securities at fair value on the balance sheet, unrealized gains increase equity, which then allows a bank to raise debt and expand. If a crisis hits, banks are in a worse position to deal with distress and the disproportional reduction of debt further magnifies problems in the financial system. As Acharya and Ryan (2016) point out, it is theoretically not clear why banks should change their book leverage in the same direction as unrealized changes in fair value, when the direct effect goes in the opposite direction. However, this lack of a theoretical underpinning generally does not reassure opponents of fair value accounting.

We use the approach of Adrian and Shin (2010, 2014) as the starting point for our analysis of procyclical leverage. Importantly we also adopt a banking perspective and focus on book leverage, not market leverage. The literature on procyclical leverage is generally interested in the leverage that banks use to finance the existing credit on their balance sheet (loans and debt securities), for which book leverage is appropriate. We include GDP growth as a control variable since changes in GDP might simultaneously drive book leverage growth and total asset growth. We also follow the suggestion of Acharya and Ryan (2016) and examine the relation between book leverage growth and GDP growth when analyzing the determinants of procyclicality.

We examine US commercial and savings banks (holding company level) between Q1-1994 and Q1-2013. As drivers of procyclical leverage might vary for different types of banks, we split our sample into three subgroups: savings banks, commercial banks with less than 20% of total assets measured at fair value (i.e., trading assets and AfS securities), and commercial banks with more than 20% fair value assets.

We interact total asset growth and GDP growth with several accounting and regulatory variables to investigate whether these variables are associated with stronger procyclical leverage. Among the accounting variables, we focus on changes in accumulated unrealized gains and losses on AfS securities (hereafter, unrealized gains and losses on AfS securities). Very few banks in the sample hold assets for which fair value changes directly affect net income and regulatory capital such as trading assets. However, almost all banks hold sizable portfolios of AfS securities that are recognized at fair value and for which changes in fair value affect banks' book equity. The accounting variables have a direct inverse effect on book leverage, as book equity (mechanically) increases in net income and in unrealized gains and losses on AfS securities. More interesting are the interaction terms of the accounting variables with total asset growth and GDP growth. Among the bank regulatory variables, we focus on the lagged regulatory capital ratio, changes in average risk-weighted assets, and the lagged book leverage ratio, which is used in regulating US banks.

We find that total asset growth and GDP growth are both positively related to book leverage growth. Our evidence is not consistent with the notion that recognizing unrealized gains and losses on AfS securities as stipulated by fair value accounting contributes to procyclical leverage or that historical cost accounting reduces procyclicality. In contrast, procyclical leverage is primarily driven by banks' business model, their intermediation function of providing loans and collecting deposits, and the volume of certain banking activities (e.g., loan sales).

Banks' business model of providing loans and collecting deposits is inherently procyclical. First, inflows and outflows of deposits directly imply a positive association between total asset growth and leverage growth, unless banks counterbalance the direct effect by adjusting their capital structure. Second, lending opportunities become more profitable and less risky if GDP growth is higher, and banks might optimally respond by increasing leverage and expanding lending.

When we look at balance sheet expansions as well as at periods of positive GDP growth, the interaction terms of unrealized gains on AfS securities with both measures are insignificant for the full sample and the different types of banks.[3] For balance sheet contractions, the interactions with unrealized gains on AfS securities are significant in some specifications. However, the signs of these coefficients are not consistent with the idea that unrealized losses force banks to reduce their book leverage (and asset holdings). In contrast, realized gains on loan sales are positively associated with procyclical leverage when commercial banks with less than 20% fair value assets expand their balance sheet, consistent with banks selling whole loans for securitization purposes. Moreover, we find that banks consider the potential obligations from off-balance sheet loan commitments as they are associated with more conservative book leverage and weaker procyclicality for balance sheet expansions and contractions.

The regulatory variables are associated with procyclical leverage. The interaction terms of commercial banks' regulatory capital (and book leverage) ratios with changes in total assets are positive (negative) and significant for balance sheet expansions, suggesting that

[3] Xie (2016) finds that the correlation between GDP growth and unrealized gains on AfS securities is weak. However, there is a direct positive relation between total asset growth and unrealized AfS gains. Consequently, the insignificance of the interaction terms between total asset growth and unrealized gains on AfS does not automatically follow from a lack of correlation between GDP growth and unrealized gains on AfS securities.

better-capitalized banks increase book leverage more when they expand. However, better-capitalized banks also issue more equity during economic expansions, which weakens the association between book leverage growth and positive GDP growth for these institutions. For commercial banks, the interaction terms of changes in total assets with changes in the average risk weight (of total assets) are consistent with the argument of Amel-Zadeh et al. (2016) that banks which increase their balance sheet can increase book leverage if the average risk weight decreases.

Irrespective of the change in average risk-weighted assets, banks may view liquid securities as being less risky and therefore choose higher book leverage if the fraction of liquid assets increases. In addition, when banks reduce cash and sell liquid assets with low risk weights as a response to an outflow of deposits, both book leverage and total assets decrease mechanically while the average risk weight increases. For savings banks, the interaction of changes in total assets with changes in the average risk weight is positive and significant upon balance sheet expansions. Consistent with this finding, savings banks disproportionally increase loans, not securities, which generally have lower risk weights during the sample period, when increasing book leverage and total assets.

Related Literature. We contribute to the literature on procyclical bank leverage. Adrian and Shin (2010) use flow of funds data and document a positive relation between book leverage growth and total asset growth for US investment banks, but not for US commercial banks or US non-financial firms. Adrian and Shin (2011) and Greenlaw et al. (2008) use bank level data and also find a strong procyclical relation for US commercial banks.[4] These papers focus on the consequences of procyclicality on aggregate liquidity,

[4]These studies do not look at US non-financial firms using firm level data. When we look at US firms, excluding financials and utilities, using quarterly data from Compustat as well as the same empirical model and time period as in our bank study, we find a positive relation between book leverage growth and total asset growth. However, it is substantially weaker compared to our sample banks both in terms of economic and statistical significance (see Table IA10 in the Internet Appendix).

economic growth, and systemic risk. In contrast, our paper is the first comprehensive analysis of the determinants of procyclical leverage for US commercial and savings banks. Beccalli et al. (2015) find that the procyclical relation between total assets and book leverage is stronger for US banks if they are more involved in securitization. However, they do not consider the role of accounting or capital regulation.[5] Closest to our work is a paper by Amel-Zadeh et al. (2016), who analyze the role of changes in regulatory risk weights and fair value accounting for procyclical leverage in the spirit of Adrian and Shin (2010). They formally show that changes in average risk-weighted assets are necessary for book leverage to be procyclical if banks' regulatory capital constraint is binding and find evidence that is consistent with their model. Like us, they do not find that fair value accounting contributes to procyclical leverage. Our paper more broadly explores potential sources of procyclicality. To this end, we also investigate the relation between GDP growth and book leverage growth, include savings banks, and perform an asset- and liability-component analysis.

Xie (2016) examines whether fair value accounting increases the procyclicality of bank lending, which constitutes a large share of total bank assets. She uses approval/denial decisions on residential mortgage applications and finds no evidence that fair value accounting is associated with lower (higher) mortgage denial rates during expansionary (recessionary) periods. Behn et al. (2016) and Dou et al. (2016) provide evidence that procyclical bank regulation and consolidation of securitization entities that affect regulatory capital requirements can have sizeable effects on bank lending. The overall findings in these papers are consistent with our results on the role of fair value accounting and regulation for leverage procyclicality.

[5] Panetta and Angelini (2009) and Baglioni et al. (2013) analyze the relation between book leverage growth and total asset growth for European banks. Damar et al. (2013) investigate Canadian banks.

2 Motivation

Consider a bank that purchases debt securities with a market value (fair value) of 100 and recognizes them on the balance sheet. The bank finances the purchase with a combination of equity and debt, equal to 10 and 90 respectively.[6] In the absence of any other business activities, and assuming that the book value of debt equals the market value of debt, the book and market value of equity are also identical. In this example, the bank's market leverage equals its book leverage. The leverage ratio, defined as total assets over equity, is 10.

According to the definition of Adrian and Shin (2010), leverage is procyclical if an increase in asset growth is associated with an increase in leverage growth and vice versa. The key question is how accounting could magnify procyclical leverage such that recognizing an increase in the value of securities on the balance sheet magnifies the positive association between leverage growth and total asset growth.

Let us assume that the value of securities rises by 1 to 101. Under fair value accounting for securities, the value of the bank's book equity also rises by 1 to 11. Thus, a 1% increase in the value of securities leads to a 10% increase in the value of equity. This increase in value has a direct inverse effect on the leverage ratio, which decreases from 10 to 9.18.

Whether the increase in value of the securities increases the bank's regulatory capital depends on how the bank classifies the securities and possible prudential filters in place. We discuss the specific rules in Section 3.3.1 and consider only two extreme cases here. In the US, and many other countries, unrealized gains and losses on AfS debt securities are recognized in other comprehensive income and do not affect regulatory capital unless the securities are sold or other-than-temporarily impaired. In contrast, unrealized gains

[6] This example is based on Adrian and Shin (2010).

and losses on trading assets go through net income and affect regulatory capital. Most banks hold very little trading assets, but even if the bank in the example had classified its securities as trading assets, it still could not have increased its leverage above 10 with a binding regulatory capital constraint, unless the average risk weight of new securities were lower than that of current securities.[7]

Banks' regulatory capital constraint is generally not strictly binding as banks typically hold regulatory capital in excess of requirements. This buffer may fluctuate with economic conditions and the risk of recognized assets.[8] Moreover, margin requirements and haircuts are generally lower in booms when asset values are high than in busts when asset values are low (e.g., Geanakoplos (2003), Fostel and Geanakoplos (2008), Geanakoplos (2010), and Gorton and Metrick (2012)). Thus, the level of borrowing and the value of securities are positively related. This procyclicality can spill over to a bank that holds these securities on its balance sheet. Banks face explicit margin requirements when borrowing against assets they pledge as collateral, as well as implicit margin requirements when borrowing to finance the portfolio of assets they hold on their balance sheet.[9]

Assume that the bank in our example uses collateralized financing. The haircut equals 10% so that the bank can raise debt equal to 90% of the value of the assets it pledges as collateral. The regulatory capital constraint is not binding. An increase in the market value of securities held by the bank from 100 to 101 then allows the bank to increase both

[7] Amel-Zadeh et al. (2016) show formally that if a bank's regulatory capital constraint is binding, procyclicality as measured by Adrian and Shin (2010) can only arise if the average risk weight of assets decreases (increases) upon balance sheet expansions (contractions).

[8] Brunnermeier and Pedersen (2009) show formally that book leverage can be positively related to prices. Adrian and Shin (2010) argue that countercyclical collateralization is a possible reason for their finding of procyclical leverage for investment banks.

[9] Adrian and Shin (2014) develop a model in which the regulatory capital constraint is not binding. Banks choose the maximum book leverage (implicitly) permitted by debt holders in the presence of contracting frictions. Collateral margin requirements and risk are positively related in Geanakoplos (2003) and Fostel and Geanakoplos (2008).

debt and total assets by 9, taking advantage of collateralized lending. However, this effect has nothing to do with how the securities are recognized on the balance sheet as investors care about market prices in collateralized financing, not book values. When securities are reported at fair value, the bank's book leverage does not change and stays at 10.[10] If, at the same time, security prices increase and the haircut decreases to 9%, the bank can expand both debt and total assets even further. Given the lower haircut, book leverage is procyclical. However, while fair value accounting would be associated with procyclical leverage, it is not causal for the increase in book leverage when the bank expands its balance sheet.[11]

While it is a priori not clear how unrealized gains and losses could affect the relation between total asset growth and book leverage growth, it does not mean that such a link could not exist. Opponents of fair value accounting might be concerned that fair value accounting could contribute to procyclicality in ways that are not well understood and have not yet been modeled. Xie (2016) shows that the correlation between unrealized gains and losses on AfS securities with economic cycle variables such as GDP growth is weak, potentially even negative. However, the same is not true for total assets and equity, which are both positively related to unrealized gains and losses. Moreover, the correlation with factors that could change haircuts, margin requirements, or a bank's regulatory capital buffer is not straightforward.

To understand the lending decision of banks and the leverage that banks use to provide

[10] In contrast, if securities are recognized at the historical cost of 100, book leverage increases as total assets still increase to 109 due to the purchase of the additional securities, while book equity stays at 10. Therefore, in our example, book leverage is procyclical under historical cost accounting, but not under fair value accounting.

[11] Adrian and Shin (2014) develop a model in which the regulatory capital constraint is not binding. Banks choose the maximum book leverage (implicitly) permitted by debt holders in the presence of contracting frictions. Collateral margin requirements and risk are positively related in Geanakoplos (2003) and Fostel and Geanakoplos (2008).

credit, it is important to look at the bank's book leverage (see also Adrian and Shin (2014) and Adrian et al. (2015)). Focusing on market leverage can be misleading. The market value of a bank is highly cyclical and includes the present value of its future business opportunities, stemming from, e.g., future securitization and market making, its business relations and its reputation. Geanakoplos (2010) argues that focusing on market leverage can be misleading and emphasizes the need to look at "securities leverage," which he defines as the "ratio of collateral values to the down payment that must be made to buy them" (page 6). Securities leverage has a direct effect on a bank's book leverage, in contrast to its market leverage, and Adrian et al. (2014) and Adrian et al. (2013) provide empirical evidence that book leverage is a good proxy for securities leverage. Thus, we focus on book leverage in our analysis and, unless stated otherwise, mean book leverage when we write leverage.

3 Research Questions and Empirical Strategy

3.1 Measuring Procyclical Bank Leverage

We use the approach of Adrian and Shin (2010) as the starting point for our analysis of procyclical bank leverage and estimate the following regression model, which relates the book leverage growth of bank i in quarter t to the growth of its total book assets:

$$\Delta\text{Book Leverage}_{\text{i,t}} = \alpha + \beta \cdot \Delta\text{Total Assets}_{\text{i,t}} + \gamma_{\text{i}} + \delta_{\text{t}} + \epsilon_{\text{i,t}} \quad . \tag{1a}$$

As Adrian and Shin (2010), we define ΔTotal Assets$_{\text{i,t}}$ and ΔBook Leverage$_{\text{i,t}}$ as ln[variable$_{\text{i,t}}$] - ln[variable$_{\text{i,t-1}}$]. Book leverage is the ratio of total book assets to book equity.

The coefficient of interest is β, which captures the relation between changes in total assets and changes in leverage. Procyclical leverage arises if this coefficient is positive and significant. Even though total assets enter the definition of book leverage, a positive relation between the changes in book leverage and changes in total assets is not mechanical. If total book assets increase by 1% and the level of book equity and book debt also both increase by 1%, the book leverage ratio (total book assets divided by book equity) does not change. In this case, the relation between changes in book leverage and changes in total assets is zero despite the increase in total assets. However, if book debt increases by more than 1%, while book equity increases by less than 1%, the leverage ratio rises. Now the regression coefficient of changes in total assets is positive.[12] In model (1a), α denotes the intercept, γ_{i} the bank fixed effect, δ_{t} the quarter-year fixed effect, and $\epsilon_{\mathrm{i,t}}$ the vector of regression disturbances. We estimate our empirical models by ordinary least squares and adjust standard errors for within-bank clusters (see Petersen (2009)).

We also investigate how changes in book leverage and changes in total assets are related to GDP growth. As suggested by Acharya and Ryan (2016), an important alternative way of measuring procyclical bank leverage is to link changes in leverage to changes in GDP.[13] We therefore estimate the following empirical model

$$\Delta \text{Book Leverage}_{\mathrm{i,t}} = \alpha + \beta \cdot \Delta \mathrm{GDP}_{\mathrm{t}} + \gamma_{\mathrm{i}} + \epsilon_{\mathrm{i,t}} \quad , \tag{1b}$$

where $\Delta \mathrm{GDP}_{\mathrm{t}}$ is defined as the log difference in real GDP between quarters t and t-1.

[12] We run regression models (1a) to (2) with book leverage defined as the ratio of book debt over book equity and find the same procyclical leverage patterns (untabulated).

[13] We use US real GDP growth as a proxy for the economic conditions that our sample banks face. Over our sample period, the correlations of the high yield credit spread index from BofA Merrill Lynch and the quarterly change in the S&P/Case-Shiller Home Price Index with the quarterly GDP growth are -0.58 and 0.24 respectively. For the largest (smallest) banks in our sample, a global (regional) measure of GDP growth could be a better proxy for the economic environment of these banks. However, most of the banks in our sample are large US banks, not regional banks, and we believe that US GDP growth is a good proxy even for large, globally active US banks.

Since $\Delta \mathrm{GDP_t}$ is constant across banks within each quarter, we drop the quarter-year fixed effect from regression model (1b). Going forward, we combine models (1a) and (1b) and include both ΔTotal Assets and ΔGDP as our measures of procyclical leverage:

$$\Delta \text{Book Leverage}_{\mathrm{i,t}} = \alpha + \beta \cdot \Delta \text{Total Assets}_{\mathrm{i,t}} + \zeta \cdot \Delta \mathrm{GDP_t} + \gamma_{\mathrm{i}} + \epsilon_{\mathrm{i,t}} \quad . \tag{1c}$$

To understand the relation between book assets and GDP, we estimate the following regression:

$$\Delta \text{Total Assets}_{\mathrm{i,t}} = \alpha + \beta \cdot \Delta \mathrm{GDP_t} + \gamma_{\mathrm{i}} + \epsilon_{\mathrm{i,t}} \quad . \tag{2}$$

3.2 Procyclical Leverage, Bank Business Model, and Bank Size

To understand how banks' business models affect leverage procyclicality, we differentiate between savings banks, commercial banks with less than 20% fair value assets, and commercial banks with more than 20% fair value assets. The fraction of fair value assets is defined as the sum of AfS securities and trading assets divided by total assets. To test whether procyclical leverage varies for the different types of banks, we estimate the following specifications:

$$
\begin{aligned}
\Delta \text{Book Leverage}_{\text{i,t}} = \alpha &+ \beta \cdot \Delta \text{Total Assets}_{\text{i,t}} \\
&+ \zeta \cdot \Delta \text{Total Assets}_{\text{i,t}} \cdot \mathbb{1}_{\text{Savings Bank}} \\
&+ \eta \cdot \Delta \text{Total Assets}_{\text{i,t}} \cdot \mathbb{1}_{\text{Commercial Bank>20\% FV}} \\
&+ \theta \cdot \Delta \text{Total Assets}_{\text{i,t}} \cdot \text{Bank Size}_{\text{i,t-1}} \\
&+ \iota' \cdot \text{Z}_{\text{i,t}} + \kappa \cdot \Delta \text{GDP}_{\text{t}} + \epsilon_{\text{i,t}}
\end{aligned} \tag{3a}
$$

$$
\begin{aligned}
\Delta \text{Book Leverage}_{\text{i,t}} = \alpha &+ \beta \cdot \Delta \text{GDP}_{\text{t}} \\
&+ \zeta \cdot \Delta \text{GDP}_{\text{t}} \cdot \mathbb{1}_{\text{Savings Bank}} \\
&+ \eta \cdot \Delta \text{GDP}_{\text{t}} \cdot \mathbb{1}_{\text{Commercial Bank>20\% FV}} \\
&+ \theta \cdot \Delta \text{GDP}_{\text{t}} \cdot \text{Bank Size}_{\text{i,t-1}} \\
&+ \iota' \cdot \text{Z}_{\text{i,t}} + \kappa \cdot \Delta \text{Total Assets}_{\text{i,t}} + \epsilon_{\text{i,t}} \quad .
\end{aligned} \tag{3b}
$$

$\mathbb{1}_{\text{Savings Bank}}$ and $\mathbb{1}_{\text{Commercial Bank>20\% FV}}$ are indicator variables that equal one if the institution is a savings bank or commercial bank with more than 20% fair value assets, and zero otherwise. The coefficients of the interaction terms with $\Delta\text{Total Assets}_{\text{i,t}}$ or $\Delta\text{GDP}_{\text{t}}$ quantify the difference in procyclicality between the respective bank type and commercial banks with less than 20% fair value assets (omitted category). We do not include a bank fixed effect since it is perfectly collinear with the bank type dummies.

The average savings bank is smaller than the average commercial bank, and commercial banks with a high fraction of fair value assets tend to be larger than commercial banks with a smaller fraction of fair value assets. To ensure that differences in size do not affect our inferences about the role of bank types, we include the logarithm of lagged total assets

(Bank $Size_{i,t-1}$) as control variable and interaction term. The vector $Z_{i,t}$ contains the stand-alone values of the business model dummies as well as Bank $Size_{i,t-1}$.

3.3 The Effects of Accounting and Bank Regulation on Procyclical Leverage

3.3.1 Institutional and Regulatory Background

FAS 115, effective in Q1-1994, requires that trading assets and AfS securities are recognized at fair value. For trading assets, changes in market value are recognized in the income statement and directly affect the bank's Tier 1 capital. In contrast, unrealized gains and losses on AfS securities are recognized not in the income statement, but rather in accumulated other comprehensive income, a special component of shareholders' equity. A change in the fair value of an AfS security affects net income when the security is sold or if an unrealized fair value loss is deemed other than temporary.

US bank regulators employ prudential filters that limit the effect of changes in the value of AfS securities on banks' regulatory capital. Unrealized gains and losses on AfS debt securities that are recognized in accumulated other comprehensive income do not affect regulatory capital. Therefore, changes in the value of AfS debt securities affect Tier 1 capital only if they are deemed other than temporarily impaired or are sold, in which cases gains and losses are realized. In contrast, unrealized losses on AfS equity securities directly reduce Tier 1 capital. On average, the AfS portfolio of our sample banks consists of 97% debt and only 3% equity securities.

During our sample period from Q1-1994 to Q1-2013, US banks had to comply with the regulatory capital requirements of the Basel I Accord.[14] Basel I requires that banks have a total regulatory capital ratio of at least 8% to be considered adequately capitalized. The total regulatory capital ratio is defined as total regulatory capital (Tier 1 capital plus supplementary (Tier 2) capital) divided by risk-weighted assets. Individual asset amounts are multiplied by fixed, predetermined risk weights (e.g., 0% for cash, 50% for mortgage loans, and 100% for corporate loans) to calculate the bank's overall risk-weighted assets. Under Basel I, changes in average risk weights for a bank over time are mainly due to changes in the portfolio of assets held by the bank. In addition to the Basel I rules, US federal banking agencies require US banks to comply with a leverage ratio requirement based on their book leverage.

3.3.2 Baseline Regression Model

To address the role of regulation and accounting, we estimate the following two specifications:

$$\begin{aligned}
\Delta\text{Book Leverage}_{\text{i,t}} = \alpha &+ \beta \cdot \Delta\text{Total Assets}_{\text{i,t}} \\
&+ \zeta' \cdot \Delta\text{Total Assets}_{\text{i,t}} \cdot \text{Accounting Items}_{\text{i,t}} \cdot \mathbb{1}_{\Delta\text{Total Assets}>0} \\
&+ \eta' \cdot \Delta\text{Total Assets}_{\text{i,t}} \cdot \text{Accounting Items}_{\text{i,t}} \cdot \mathbb{1}_{\Delta\text{Total Assets}<0} \\
&+ \theta' \cdot \Delta\text{Total Assets}_{\text{i,t}} \cdot \text{Regulatory Items}_{\text{i,t(-1)}} \cdot \mathbb{1}_{\Delta\text{Total Assets}>0} \\
&+ \iota' \cdot \Delta\text{Total Assets}_{\text{i,t}} \cdot \text{Regulatory Items}_{\text{i,t(-1)}} \cdot \mathbb{1}_{\Delta\text{Total Assets}<0} \\
&+ \kappa' \cdot \text{W}_{\text{i,t}} + \lambda' \cdot \text{X}_{\text{i,t}} + \mu \cdot \Delta\text{GDP}_{\text{t}} + \gamma_{\text{i}} + \epsilon_{\text{i,t}}
\end{aligned} \tag{4a}$$

[14] The accord was released in July 1988. In the US, banks first had to adapt the full standard by the end of 1992 (Basle Committee on Banking Supervision (1988)). The financial crisis and regulatory discussions about Basel III led to a delay in the implementation of Basel II and by Q1-2013 (end of our sample period), no US bank had implemented the Basel II rules (KPMG (2013)).

$$
\begin{aligned}
\Delta\text{Book Leverage}_{\text{i,t}} = \alpha + \beta \cdot \Delta\text{GDP}_{\text{t}} \\
&+ \zeta' \cdot \Delta\text{GDP}_{\text{t}} \cdot \text{Accounting Items}_{\text{i,t}} \cdot \mathbb{1}_{\Delta\text{GDP}>0} \\
&+ \eta' \cdot \Delta\text{GDP}_{\text{t}} \cdot \text{Accounting Items}_{\text{i,t}} \cdot \mathbb{1}_{\Delta\text{GDP}<0} \\
&+ \theta' \cdot \Delta\text{GDP}_{\text{t}} \cdot \text{Regulatory Items}_{\text{i,t(-1)}} \cdot \mathbb{1}_{\Delta\text{GDP}>0} \\
&+ \iota' \cdot \Delta\text{GDP}_{\text{t}} \cdot \text{Regulatory Items}_{\text{i,t(-1)}} \cdot \mathbb{1}_{\Delta\text{GDP}<0} \\
&+ \kappa' \cdot \text{W}_{\text{i,t}} + \lambda' \cdot \text{X}_{\text{i,t}} + \mu \cdot \Delta\text{Total Assets}_{\text{i,t}} + \gamma_{\text{i}} + \epsilon_{\text{i,t}} \quad .
\end{aligned}
\tag{4b}
$$

Each interaction term measures the association between procyclical leverage and the respective accounting or regulatory items. In this context, we differentiate between increases and decreases in total assets and GDP to capture potential differing elasticities between expansions and contractions.

In the baseline model, the vector Accounting $\text{Items}_{\text{i,t}}$ contains changes in accumulated unrealized gains and losses on AfS securities (hereafter, unrealized gains and losses on AfS securities) as well as net income.[15] AfS securities is by far the largest reporting class that is recognized at fair value. Therefore, we focus on AfS securities in our analysis of the role of accounting.[16] In the supplementary section, we perform additional tests that involve splits of unrealized gains and losses on AfS securities into its debt and equity components. We normalize all accounting items by lagged total assets and multiply them by 1000.

Unrealized gains (losses) on AfS securities and positive (negative) net income both have a direct negative (positive) effect on leverage. Important for the understanding of procyclical leverage are the coefficients of the interactions of these variables with ΔTotal

[15] Once an AfS security is sold, the realized gain or loss moves from unrealized gains and losses on AfS securities to net income. In Tables IA11 and IA12 of the Internet Appendix, we split net income into realized gains and losses on AfS and HtM securities as well as residual net income and find that our inferences remain unchanged.

[16] Only very few banks hold sizable trading assets. In untabulated results that we discuss in Section 5, we also consider trading assets and assets for which the bank chose the fair value option that FAS 159 introduced in 2008, with early adoption allowed as of 2007.

$\text{Assets}_{i,t}$ and ΔGDP_t. A significant positive coefficient on an interaction term implies that the variable is associated with procyclicality. Changes in the market values of AfS securities could be associated with procyclicality independent of how they are recognized. Thus, a significant positive coefficient on unrealized gains and losses on AfS securities does not imply that recognizing these securities at historical cost would reduce procyclicality. If the coefficient on an interaction term with unrealized gains and losses of AfS securities is insignificant, changes in fair values (market values) of these securities are not associated with procyclicality despite the recognition of the value changes on the balance sheet.

The vector $\text{Regulatory Items}_{i,t(-1)}$ contains the bank's lagged total regulatory capital ratio, the change in average risk-weighted assets, and the lagged book leverage ratio. The average risk weight equals the ratio of risk-weighted assets to total assets. $\Delta\text{Risk Weight}_{i,t}$ is defined as the difference in the log of the average risk weight. For expositional purposes, we multiply both the total capital ratio and $\Delta\text{Risk Weight}_{i,t}$ with 100.

If regulatory capital is high and leverage is low, banks are less constrained from increasing leverage when they expand so we expect the relation between $\Delta\text{Total Assets}_{i,t}$ and $\Delta\text{Book Leverage}_{i,t}$ to be stronger. When interacting $\Delta\text{Risk Weight}_{i,t}$ with $\Delta\text{Total Assets}_{i,t}$, it is important to distinguish between increases and decreases of the balance sheet. If changes in average risk-weighted assets magnify procyclical leverage, the coefficient of the interaction term should be negative and significant upon balance sheet expansions since a decrease in average risk-weighted assets allows banks to increase leverage. In contrast, when balance sheets contract, a positive and significant interaction term is consistent with banks using liquid assets with low risk weights to repay debt.

The vector W contains the stand-alone values of the interacted accounting and regulatory items in the respective specification. X denotes the vector of control variables, which includes $\text{Bank Size}_{i,t\text{-}1}$, $q_{i,t\text{-}1}$, and $\Delta\text{Goodwill}_{i,t}$. $q_{i,t\text{-}1}$ is defined as the lagged market-to-book ratio of equity to capture the bank's market value of equity. $\Delta\text{Goodwill}_{\text{i,t}}$ is defined as the fraction of [$\text{Goodwill}_{\text{i,t}}$ - $\text{Goodwill}_{\text{i,t-1}}$] to |$\text{Total Assets}_{\text{i,t}}$ - $\text{Total Assets}_{\text{i,t-1}}$| and controls for mergers & acquisitions.[17]

3.4 Asset and Liability Decomposition of Procyclical Leverage, Off-Balance Sheet Obligations, and Loan Sales

To understand the drivers of procyclical leverage, we study which types of assets are associated with procyclical expansions and contractions of the balance sheet. To do so, we split ΔTotal Assets from model (1a) into the quarterly growth rates of loans, securities, and cash. Banks may expand via securities or loans. Expansions of securities are consistent with a decrease in the average risk weight or a lower perceived risk and higher liquidity of these assets. Expansions of loans are consistent with procyclical leverage being associated with the standard business model of banks and loan origination for securitization. For balance sheet contractions, it is interesting to examine whether cash and securities decrease.

To investigate how banks finance procyclical balance sheet expansions and which types of liabilities banks reduce upon procyclical contractions, we replace ΔTotal Assets in model (1a) with the quarterly changes of deposits, senior debt, and subordinated debt. For both expansions and contractions, it is illustrative to see whether they are associated with changes in deposits or other sources of debt financing.

As discussed by Acharya and Ryan (2016), banks often hold off-balance sheet obliga-

[17] We use the growth of a bank's goodwill as a control since the goodwill of the combined/surviving entity typically increases strongly after mergers & acquisitions. The residual of the purchase price and book value of net assets is recognized as goodwill in acquisitions since 1970 (purchase transactions; APB Opinion No. 16) and in mergers since 2001 (previously pooling transactions; FAS 141). Many small banks in our sample have zero goodwill on their balance sheet such that ΔGoodwill based on log differences is not defined for these banks. To overcome this problem, we use the above definition of ΔGoodwill, which is economically very similar, but has the benefit that |$\text{Total Assets}_{\text{i, t}}$ - $\text{Total Assets}_{\text{i, t-1}}$| is positive and typically non-zero. Our inferences remain unchanged if we do not control for $\Delta\text{Goodwill}_{\text{i,t}}$.

tions that require them to provide funding upon occurrence of specific triggering events. We look at (i) loan commitments and (ii) off-balance sheet securitized assets, where the latter is used as proxy for credit/liquidity support in securitizations, to test whether banks consider these off-balance sheet obligations when choosing balance sheet leverage and to estimate how these off-balance sheet obligations interact with procyclical leverage. In addition, we investigate the relation between procyclical leverage and realized gains on loan sales. Banks sell loans in the process of securitization and realized gains on loans sales are related to the volume and profitability of banks' securitization activities.

4 Data

4.1 Data Sources and Sample Selection

We obtain our bank-level data from the bank fundamentals database of *SNL Financial* and the real GDP data from the homepage of the *Bureau of Economic Analysis* (BEA). SNL's bank database contains detailed information about the balance sheet and income statement of all active, acquired/defunct and listed/non-listed US financial institutions that report to the SEC, the Federal Reserve System, the FDIC, or the Comptroller of the Currency. We focus on US commercial and savings banks at the holding company level that file Y-9C and 10-Q reports and download data for all commercial bank holding companies and savings and loan holding companies from *SNL Financial.* Our sample covers the time period from Q1-1994 to Q1-2013.[18]

[18] Savings banks include thrifts and mutual banks. Broker-dealers that became bank holding companies during the financial crisis (e.g., Goldman Sachs and Morgan Stanley) are not included in the sample. Broker-dealers acquired by commercial or savings banks are included in the sample. For example, Merrill Lynch was a pure broker-dealer before its acquisition by Bank of America in 2009. We do not include Merrill Lynch in our sample before 2009. However, Merrill Lynch implicitly became part of our sample once it had been absorbed by Bank of America. There are very few such cases.

To be included in our sample, we require that bank-quarter observations have (i) non-missing and positive values for total assets and book equity, (ii) non-missing values for book leverage growth and total asset growth, (iii) total assets in excess of $150 million, and (iv) in the case of commercial banks, non-missing values for the fraction of fair value assets. These selection criteria result in an initial sample of 41,748 bank-quarter observations for 932 banks. Focusing our attention on banks for which all regression variables in models (4a) and (4b) are non-missing reduces our sample to 26,034 bank-quarter observations for 819 banks. To mitigate the effects of outliers, we winsorize all bank-level ratios, growth rates, and accounting items at the 1st and 99th percentiles.

4.2 Descriptive Statistics

Table 1 reports the mean (average) and median of various balance sheet characteristics and regulatory variables for our sample banks. The average total assets is $10.69 billion. With average total assets of $1.95 billion, savings banks are smaller than commercial banks. Among commercial banks, those with more than 20% fair value assets are significantly larger, with average total assets of $22.42 billion. The average book leverage ratio is 11.26 and thus lower than the book leverage of large US investment banks, which Figure 16 in Adrian and Shin (2010) indicates is in the range of 20 to 35. The average savings bank has a higher regulatory capital ratio and a lower book leverage ratio than the average commercial bank. Loans are the largest asset class, at 66.13% of total bank assets on average. AfS securities are the next largest asset class, at 17.51% of total assets. HtM securities only equal 3.67% of total assets. Trading assets play a minor role for most banks in our sample, on average equaling 0.10% of total assets. Deposits is the dominant source of funding, with 77.53% of total assets, followed by senior debt with 10.49% of total assets.

Table 2 shows summary statistics for the key variables of our empirical analysis. Between Q1-1994 and Q1-2013, the average growth of GDP, total assets, and book leverage was 0.50%, 1.87%, and 0.13% per quarter. Average realized gains on loans (0.03% of total assets) are larger than unrealized gains on AfS securities (0.004%), but these have a higher standard deviation.

5 Results

Figure 1 plots ΔTotal Assets and ΔBook Leverage for all bank-quarter observations of our sample and Figure IA1 in the Internet Appendix depicts the same relation for each bank type. The graphs show strong procyclical leverage patterns. Table 3 reports the estimation results for regression models (1a) to (2), and variations thereof. The coefficients of ΔTotal Assets and ΔGDP are positive and highly statistically significant for the stand-alone specifications as well as for the model in which both variables are included simultaneously. Thus, banks increase (decrease) book leverage when they expand (contract) their balance sheet and when economic conditions improve (deteriorate). In terms of economic magnitude, the estimates in columns [1] and [3] imply that increases in total asset growth and GDP growth by one standard deviation are associated with increases in book leverage growth by 0.35 and 0.07 standard deviations, respectively. The coefficient of the interaction term between changes in total assets and changes in GDP is not significant. The positive relation between ΔTotal Assets and ΔBook Leverage is significantly stronger for balance sheet contractions than expansions. The difference in coefficients is 0.217 and the p-value of the null hypothesis that this difference is zero equals 0.03%. In contrast, we do not find that the association between ΔGDP and ΔBook Leverage is stronger during economic contractions (difference: 0.062; p-value: 76.94%). Total asset growth and GDP growth are positively related. While this effect is particularly strong for quarters of positive GDP growth, it turns negative during recessions (negative GDP growth). As we discuss in greater detail in Section 6.1, the increase in total assets during the recent financial crisis is mainly driven by an inflow of deposits and Troubled Asset Relief Program (TARP) funds.

In Table 4, we report the results of regression models (3a) and (3b). Compared to commercial banks with less than 20% fair value assets, the procyclical relation between ΔTotal Assets and ΔBook Leverage is significantly stronger for savings banks and commercial banks with more than 20% fair value assets. There is no statistically significant difference in coefficients between commercial banks with more than 20% fair value assets and savings banks. The relation between ΔGDP and ΔBook Leverage is significantly weaker for savings banks and strongest for commercial banks with more than 20% fair value assets. The results are robust to controlling for bank size. The finding that savings banks show a strong positive relation between ΔTotal Assets and ΔBook Leverage and a weak positive relation between ΔGDP and ΔBook Leverage could be related to their high reliance on deposit financing and high costs of adjusting their capital structure (high cost of raising equity and low share of short-term subordinate debt outstanding). When deposits increase, total assets and leverage increase if savings banks do not adjust their leverage. When GDP growth increases, savings banks might find it costly to expand or increase leverage.

In Table 5, we focus on the relation between total asset growth and book leverage growth (model (4a)). The interaction terms of ΔTotal Assets with unrealized gains and losses on AfS securities are not statistically significant for the full sample and all subsamples when banks expand their balance sheet. Upon balance sheet contractions, the interaction is statistically significant and positive for the full sample and savings banks. In untabulated results, we find that the effect is driven by unrealized gains, not losses. Overall, higher unrealized fair value gains (losses) on AfS securities do not magnify the procyclical leverage pattern when banks expand (contract) their balance sheet.[19]

Regulatory capital (book leverage) interacts positively (negatively) with ΔTotal Assets when banks expand their balance sheets. This finding is consistent with better-capitalized banks being less constrained from increasing leverage when they expand. For balance sheet contractions, the interaction terms are not statistically significant. Moreover, we find that the interaction terms of net income with ΔTotal Assets are positive.

The interaction of changes in average risk-weighted assets with changes in total assets is negative and significant upon balance sheet expansions for the full sample. This finding is in line with the argument that the positive relation between ΔTotal Assets and ΔBook Leverage arises if an expansion of the balance sheet accompanies a decrease in the average risk weight, e.g., because these banks hold more cash or invest in securities with low risk weights. However, for savings banks, the coefficient is positive. This result suggests that savings banks disproportionally increase loans when expanding their balance sheet, which is consistent with the findings of our asset-component analysis below (Panel A of Table 7). When banks shrink their balance sheet, the interaction of ΔTotal Assets with ΔRisk Weight is positive and significant for the full sample and both types of commercial banks. The increase in average risk weight might force banks to disproportionally reduce leverage, given a binding leverage constraint. However, it is also possible that the coefficient captures the mechanical effect of banks reducing cash and selling liquid assets (both have low risk weights) as a response to an outflow of deposits, which is consistent with our findings in

[19] We run two separate regressions for a subsample of banks with positive trading assets. In untabulated results we find that the interaction terms of trading income with ΔTotal Assets are significant and positive for balance sheet expansions, but insignificant for contractions. Trading income includes realized gains and losses from the sale of trading assets and fee income from non-proprietary trading activities. Thus, trading income is not a clean measure of unrealized fair value gains and losses. Including income from assets held under the fair value option, which only contains unrealized gains and losses, reduces the significance of the coefficient. We do not find that trading income or the sum of trading income and unrealized gains and losses from assets held under the fair value option magnify the relation between ΔBook Leverage and ΔGDP.

Panel B of Table 7.

In Table 6, we investigate the relation between GDP growth and book leverage growth. For now, our discussion focuses on periods of positive GDP growth. We look at the interactions for periods of negative GDP growth in Section 6.1. The interaction terms with unrealized gains and losses on AfS securities are statistically insignificant during economic expansions both for the full sample and all types of banks. Therefore, unrealized fair value gains do not seem to contribute to the procyclical relation between GDP growth and book leverage growth. These findings are consistent with Xie (2016), who shows that, if anything, unrealized net gains on AfS securities tend to be countercyclical. The coefficients of the interaction terms with net income are insignificant.

Interestingly, the interactions with total regulatory capital are negative and significant for the total sample and commercial banks with less than 20% fair value assets. The significant negative coefficient for these banks suggests that book leverage increases less during economic expansions if banks have a higher regulatory capital ratio. The coefficients of the interaction with the leverage ratio are insignificant. One possible explanation is that it is easier for well capitalized banks to obtain equity financing during times of higher GDP growth. Indeed, in untabulated tests we find that if we replace ΔBook Leverage by the amount of equity issued, the relation between equity issuance and ΔGDP is significantly stronger for well capitalized banks. Finally, the interaction with ΔRisk Weight is insignificant during economic expansions.

Panel A of Table 7 provides the estimation results for our asset-component analysis. For balance sheet expansions, the coefficient of ΔLoans is the largest (highly significant) across all banks and asset types. This result is not related to the fact that loans are the largest asset class on the balance sheet as the regression coefficient captures the sensitivity of book leverage to percentage changes in loans. For balance sheet contractions, the coefficient of ΔLoans is not significant. Consequently, banks disproportionally expand loans, not securities, when they increase book leverage and total assets. In contrast, banks in our sample reduce securities and cash upon procyclical balance sheet contractions. In Panel B of Table 7, we find that the positive relation between ΔTotal Assets and ΔBook Leverage is mainly associated with disproportional expansions and contractions of deposits. Inflows (outflows) of deposits lead to a direct increase (decrease) in total assets and book leverage. Thus, procyclical leverage is inherently linked to inflows and outflows of deposits as part of banks' general business model.

In Table 8, we report our results for the effects of off-balance sheet obligations and realized gains on loan sales on procyclical leverage. We find that banks with a higher increase in loan commitments have a lower book leverage ratio. Similarly, an increase in loan commitments dampens procyclicality when banks increase their balance sheet. Therefore, banks that expand both on-balance sheet assets and off-balance sheet loan commitments increase book leverage by less than banks that do not increase their loan commitments. In contrast, a higher growth in loan commitments is associated with stronger procyclical balance sheet contractions. Our findings on loan commitments suggest that these potential obligations are taken into account by banks as they are associated with more conservative book leverage. The interaction term of ΔTotal Assets with realized gains on loan sales is positive and highly statistically significant for balance sheet expansions. This evidence suggests an association between liquidity in secondary loan markets, loan growth, and leverage procyclicality. The interaction terms of loan commitments with ΔGDP as well as the coefficients for off-balance sheet securitized assets and its interactions are not significant.

6 Supplementary Analyses

6.1 The Crisis of 2007-2009 and Government Interventions

We take a closer look at the inverse relation between ΔGDP and ΔTotal Assets during periods of negative GDP growth, which implies that bank assets increase during recessions. Our analysis highlights that this result is driven by the financial crisis of 2007-2009 (Panel A of Table IA2, where "IA" refers to tables in the Internet Appendix). If we exclude quarters with negative GDP growth that stem from the crisis of 2007-2009, the relation between ΔGDP and ΔTotal Assets also becomes positive during recessions.

We find that it is mainly inflows of deposits but also government sponsored capital injections in the form of TARP that explain the increase in total assets during the crisis in quarters with negative GDP growth (Panel B of Table IA2). The results for deposits are in line with the evidence by Acharya and Mora (2015), who document a large inflow of funds into the banking sector in the form of deposits at the end of 2008 and in 2009. We find a weak positive association between changes in loan commitments and changes in total assets during this time. Therefore, increases (decreases) in loan commitments are associated with expansions (contractions) of total assets. One possible explanation is that banks that increased their balance sheet were able to expand loan commitments, while banks that contracted their balance sheet experienced drawdowns and revocations of loan commitments. Drawdowns do not result in an increase of total assets if banks use cash or liquid securities, and not external funds, to finance the drawdowns. Off-balance sheet securitized assets are not significantly related to balance sheet expansions or contractions during the financial crisis.

The leverage dynamics of banks that received TARP funds after the Lehman bankruptcy are very different compared to institutions that did not receive TARP funds (Table IA3). Banks that received TARP equity between Q4-2008 and Q2-2009 exhibit a strong reduction of book leverage induced by the government funds. In contrast, non-TARP banks increased their book leverage over the same period.

When interpreting the interaction terms with ΔGDP during recessions, it is important to distinguish between banks that received TARP funds and those that did not. We introduce the indicator variable $\mathbb{1}_{\mathrm{TARP\_BANK\_QRT}_{i,t}}$, which is equal to one if bank i received TARP injections in quarter t, and zero otherwise. We then run a modified version of regression model (4b), in which we estimate the interactions for negative GDP growth (i) for quarters in which the leverage of TARP banks was affected by direct government interventions and (ii) for all other contractionary quarters. We find that most of the significant interaction terms during recessions stem from bank quarters that were impacted by TARP interventions (Table IA4). For recessionary bank-quarters that were not affected by TARP capital infusions, unrealized fair value losses on AfS securities still do not magnify the link between ΔGDP and ΔBook Leverage. The negative and significant interaction term for commercial banks with less than 20% fair value assets that did not receive TARP funds is driven by large unrealized gains on AfS securities in 2009, which resulted from a decrease in interest rates (untabulated; see also Xie (2016)). The coefficient of the interaction with the total capital ratio is negative and significant for those recessionary bank-quarters that are not affected by direct government intervention. This finding is in line with the intuition that weakly-capitalized banks have to delever more quickly in economic downturns due to binding regulatory capital constraints.

6.2 Alternative Measures of Banks' Business Model

We add a bank's mortgage exposure, consumer loans exposure, and commercial real estate exposure as well as the share of interest to non-interest income as alternative proxies for the bank's business model to regressions (3a) and (3b). We interact these variables with ΔTotal Assets and ΔGDP to see whether the estimates are significant and whether the coefficients of the interactions with savings banks and commercial banks with more than 20% fair value assets drop in significance when adding the alternative business model proxies. As a reference case, we first estimate our regressions for the bank quarters in which the business model proxy is available without including the variable. The objective is to verify that the coefficients of the interaction terms for savings banks and commercial banks with more than 20% fair value assets are significant and have the same sign as in the full sample in Table 4.

When we include banks' commercial real estate exposure as additional variable (Table IA5), the coefficient of the interaction with ΔTotal Assets is negative and significant. Therefore, banks with a higher share of commercial real estate lending exhibit less procyclicality. Commercial real estate loans carry a high risk weight of 100%. Compared to mortgages and securities (risk weights of 50% or less), banks that originate many commercial real estate loans need to hold more capital against these assets, which weakens the positive association between total asset growth and leverage growth. The coefficients of the interactions with savings banks and commercial banks with more than 20% fair value assets, which were previously positive and significant, become insignificant. This result suggests that variation in the share of commercial real estate exposure can explain some of the difference in procyclical leverage between commercial banks with less than 20% fair value assets and the other two types of banks.[20] The interaction terms of our measures of banks' business model with ΔGDP are all insignificant.

6.3 Derivatives and AfS Equity Securities

We investigate whether there is a significant increase in procyclical leverage around two institutional changes that imply an increased relevance of fair value accounting for regulatory capital and the recognition of assets. First, unrealized gains on AfS equity securities initially did not affect regulatory capital. However, since Q4-1998, the Fed permits banks to include up to 45% of the pre-tax net unrealized holding gains on AfS equity securities in Tier 2 capital, which is part of total regulatory capital. Second, with a few exceptions, derivatives that banks held for hedging purposes were not recognized at all or recognized under synthetic instrument accounting until the introduction of FAS 133, which became effective in Q1-2001, with early adoption allowed as of Q3-1998. FAS 133 requires banks to classify derivatives held for accounting hedging purposes as fair value hedges or cash flow hedges. The accounting treatment of fair value hedges is comparable to the treatment of trading assets, and the treatment of cash flow hedges is comparable to the treatment of AfS securities.

In the Internet Appendix, we test whether these two institutional changes increased leverage procyclicality. Moreover, we rerun regression models (4a) and (4b), splitting total unrealized gains and losses on AfS securities into their debt and equity components and including unrealized gains and losses on cash flow hedges. Overall, our evidence does not support the conclusion that FAS 133 and the partial removal of the prudential filter for AfS equity securities resulted in stronger procyclicality. Moreover, we do not find that

[20] As a plausibility check, we verify that commercial banks with less than 20% fair value assets have a higher exposure to commercial real estate than savings banks and commercial banks with more than 20% fair value assets.

unrealized gains and losses on (i) cash flow hedges and (ii) AfS equity and debt securities magnify procyclical leverage.

7 Conclusion

We investigate the determinants of procyclical book leverage for US commercial and savings banks between Q1-1994 and Q1-2013, focusing on the role of accounting and regulation. We follow Adrian and Shin (2010, 2014) and measure procyclical bank leverage as the relation between quarterly book leverage growth and total asset growth. The approach is used in several articles, and regulators as well as the business press often refer to it. Procyclical leverage arises if an increase in the growth rate of total assets is associated with an increase in the growth rate of book leverage. In addition, we also investigate the relation between quarterly book leverage growth and GDP growth.

We find that total asset growth and GDP growth are both positively related to book leverage growth. While the positive relation may capture lower risk and better lending opportunities that result in more lending and higher leverage when economic conditions improve, there is a concern that accounting and bank regulation could magnify these associations.

Our evidence is not consistent with the notion that recognizing unrealized gains and losses on AfS securities as stipulated by fair value accounting contributes to procyclical leverage or that historical cost accounting reduces procyclicality. In contrast, procyclical leverage is primarily driven by banks' business models, their intermediation function of providing loans and collecting deposits, and the volume of certain banking activities (e.g., loan sales).

References

Acharya, V. and S. G. Ryan (2016). Banks' Financial Reporting and Financial System Stability. *Journal of Accounting Research 54*(2), 277–340.

Acharya, V. V. and N. Mora (2015). A Crisis of Banks as Liquidity Providers. *Journal of Finance 70*(1), 1–43.

Adrian, T., N. Boyarchenko, and H. S. Shin (2015). The Cyclicality of Leverage. *Working Paper, Federal Reserve Bank of New York*.

Adrian, T., E. Etula, and T. Muir (2014). Financial Intermediaries and the Cross-Section of Asset Returns. *Journal of Finance 69*(6), 2557–2596.

Adrian, T., E. Moench, and H. S. Shin (2013). Dynamic Leverage Asset Pricing. *Working Paper, Federal Reserve Bank of New York*.

Adrian, T. and H. S. Shin (2010). Liquidity and Leverage. *Journal of Financial Intermediation 19*(3), 418–437.

Adrian, T. and H. S. Shin (2011). Financial Intermediary Balance Sheet Management. *Annual Review of Financial Economics 3*, 289–307.

Adrian, T. and H. S. Shin (2014). Procyclical Leverage and Value-at-Risk. *Review of Financial Studies 27*(2), 373–403.

Amel-Zadeh, A., M. E. Barth, and W. R. Landsman (2016). The Contribution of Bank Regulation and Fair Value Accounting to Procyclical Leverage. *Working Paper, Stanford University*.

Badertscher, B. A., J. J. Burks, and P. D. Easton (2012). A Convenient Scapegoat: Fair Value Accounting by Commercial Banks During the Financial Crisis. *The Accounting Review 87*(1), 59–90.

Baglioni, A. S., E. Beccalli, A. Boitani, and A. Monticini (2013). Is the Leverage of European Banks Procyclical? *Empirical Economics 45*, 1251–1266.

Bank for International Settlements (2009). The Role of Valuation and Leverage in Procyclicality. *Committee on the Global Financial System* (34).

Barth, M. E. and W. R. Landsman (2010). How Did Financial Reporting Contribute to the Financial Crisis? *European Accounting Review 19*(3), 399–423.

Basle Committee on Banking Supervision (1988). International Convergence of Capital Measurement and Capital Standards.

Beccalli, E., A. Boitani, and S. Di Giuliantonio (2015). Leverage Pro-Cyclicality and Securitization in US Banking. *Journal of Financial Intermediation 24*(2), 200–230.

Behn, M., R. Haselmann, and P. Wachtel (2016). Procyclical Capital Regulation and Lending. *Journal of Finance 71*(2), 919–956.

Benston, G. J. (2008). The Shortcomings of Fair-Value Accounting Described in SFAS 157. *Journal of Accounting and Public Policy 27*(2), 101–114.

Bhat, G., R. Frankel, and X. Martin (2011). Panacea, Pandora's Box, or Placebo: Feedback in Bank Holdings of Mortgage-Backed Securities and Fair Value Accounting. *Journal of Accounting and Economics 52*(2-3), 153–173.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market Liquidity and Funding Liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Damar, H. E., C. A. Meh, and Y. Terajima (2013). Leverage, Balance-Sheet Size and Wholesale Funding. *Journal of Financial Intermediation 22*(4), 639–662.

Dou, Y., S. G. Ryan, and B. Xie (2016). The Real Effects of FAS 166 and FAS 167. *Working Paper, New York University*.

Economist (2008). The Financial System: What Went Wrong.

Financial Services Authority (2009). The Turner Review: A Regulatory Response to the Global Banking Crisis.

Financial Times (2008). Insight: True Impact of Mark-to-Market on the Credit Crisis.

Fostel, A. and J. Geanakoplos (2008). Leverage Cycles and the Anxious Economy. *American Economic Review 98*(4), 1211–1244.

Geanakoplos, J. (2003). Liquidity, Default, and Crashes: Endogenous Contracts in General Equilibrium. In M. Dewatripont, L. Hansen, and S. Turnovsky (Eds.), *Advances in Economics and Econometrics II*, pp. 107–205. Econometric Society.

Geanakoplos, J. (2010). The Leverage Cycle. *NBER Macroeconomics Annual 2009 24*, 1–65.

Gorton, G. and A. Metrick (2012). Securitized Banking and the Run on Repo. *Journal of Financial Economics 104*(3), 425–451.

Greenlaw, D., J. Hatzius, A. K. Kashyap, and H. S. Shin (2008). Leveraged Losses: Lessons from the Mortgage Market Meltdown. *US Monetary Policy Forum Report No. 2*.

Huizinga, H. and L. Laeven (2012). Bank Valuation and Accounting Discretion During a Financial Crisis. *Journal of Financial Economics 106*(3), 614–634.

International Monetary Fund (2008). Chapter 3: Fair Value Accounting and Procyclicality. *Global Financial Stability Report*.

KPMG (2013). Capital Management Services: Gaining Strategic Value from Regulatory Reform.

Laux, C. and C. Leuz (2009). The Crisis of Fair-Value Accounting: Making Sense of the Recent Debate. *Accounting, Organizations and Society 34*(6-7), 826–834.

Laux, C. and C. Leuz (2010). Did Fair-Value Accounting Contribute to the Financial Crisis? *Journal of Economic Perspectives 24*(1), 93–118.

Panetta, F. and P. Angelini (2009). Financial Sector Pro-Cyclicality: Lessons from the Crisis. *Banca D'Italia: Occasional Paper* (44).

Persaud, A. (2008). Regulation, Valuation and Systemic Liquidity. *Banque de France, Financial Stability Review: Special Issue on Valuation* (12).

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies 22*(1), 435–480.

Plantin, G., H. Sapra, and H. S. Shin (2008). Fair Value Accounting and Financial Stability. *Banque de France, Financial Stability Review: Special Issue on Valuation* (12).

Ryan, S. G. (2008). Accounting in and for the Subprime Crisis. *The Accounting Review 83*(6), 1605–1638.

Securities and Exchange Commission (2008). Report and Recommendations Pursuant to Section 133 of the Emergency Economic Stabilization Act of 2008: Study on Mark-to-Market Accounting.

Xie, B. (2016). Does Fair Value Accounting Exacerbate the Procyclicality of Bank Lending? *Journal of Accounting Research 54*(1), 235–274.

Tables and Figures

Table 1: Bank Characteristics
This table reports means and medians of various balance sheet characteristics and regulatory variables for our sample banks. Panel A reports asset-specific variables and Panel B lists variables which are related to the liability-side of the banks' balance sheets. In Panel A, all figures are normalized by total assets (except for total assets). In Panel B, all figures are normalized by total assets except for book leverage, the Tier 1 capital ratio, and the total capital ratio. Other financial assets include cash and equivalents (marketable securities). Other liabilities include all liabilities that cannot be classified as deposits, senior debt, or subordinated debt. The fraction of fair value assets equals the sum of trading assets and AfS securities divided by total assets. Bank fundamentals are obtained from *SNL Financial*. This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013.

	Full Sample		**Savings Banks**		**Commercial Banks < 20% FV Assets**		**Commercial Banks > 20% FV Assets**	
Panel A: Assets	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Trading Assets [%]	0.10	0.00	0.04	0.00	0.08	0.00	0.17	0.00
Available-for-Sale [%]	17.51	16.25	14.66	12.52	11.57	12.08	28.58	26.57
Held-to-Maturity [%]	3.67	0.24	5.22	0.60	4.06	0.27	2.22	0.09
Loans [%]	66.13	67.26	67.96	70.03	71.22	71.89	56.98	59.05
Other Financial Assets [%]	6.09	4.72	5.20	3.82	6.67	5.29	5.61	4.32
Total Financial Assets [%]	93.80	94.25	93.67	94.11	93.77	94.27	93.92	94.27
Risk-Weighted Assets [%]	69.63	70.05	60.91	61.64	75.17	75.76	64.96	65.30
Total Assets (US$ billion)	10.69	0.60	1.95	0.53	6.30	0.57	22.42	0.68

	Full Sample		**Savings Banks**		**Commercial Banks < 20% FV Assets**		**Commercial Banks > 20% FV Assets**	
Panel B: Liabilities	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Deposits [%]	77.53	79.60	71.29	72.49	79.86	81.64	77.13	78.94
Senior Debt [%]	10.49	8.70	15.49	13.90	8.39	6.90	10.67	9.32
Subordinated Debt [%]	0.87	0.00	0.41	0.00	1.09	0.60	0.79	0.00
Other Liabilities [%]	1.22	0.89	1.38	1.03	1.13	0.83	1.27	0.90
Total Liabilities [%]	90.35	90.83	88.79	89.78	90.69	90.99	90.65	90.93
Book Leverage	11.26	10.91	10.11	9.78	11.53	11.10	11.43	11.02
Tier 1 Capital Ratio [%]	13.72	12.58	17.17	15.11	12.49	11.75	14.16	13.40
Total Capital Ratio [%]	15.13	13.97	18.27	16.20	13.95	13.18	15.60	14.82

Table 2: Descriptive Statistics
This table reports descriptive statistics for key variables of our empirical analysis. We report the number of observations (N), mean, standard deviation (SD), 1% quantile, 25% quantile ($Q_{0.25}$), median, 75% quantile ($Q_{0.75}$), and 99% quantile ($Q_{0.99}$). Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial*. Real GDP is retrieved from the homepage of the *Bureau of Economic Analysis*. This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013.

	N	**Mean**	**SD**	$Q_{0.01}$	$Q_{0.25}$	**Median**	$Q_{0.75}$	$Q_{0.99}$
ΔGDP [%]	41748	0.50	0.68	-2.14	0.28	0.57	0.90	1.73
ΔTotal Assets [%]	41748	1.87	4.42	-8.10	-0.50	1.32	3.41	22.77
ΔBook Leverage [%]	41748	0.13	6.52	-29.21	-2.32	-0.03	2.60	23.87
ΔRisk Weight [%]	32968	0.06	3.37	-11.46	-1.60	0.18	1.82	10.53
ΔGoodwill [%]	39821	0.11	2.48	-12.69	0.00	0.00	0.00	13.89
Unrealized Gains AfS [‰]	36467	0.04	1.48	-5.31	-0.54	0.01	0.68	4.65
Net Income [‰]	41479	1.86	2.30	-10.81	1.29	2.24	3.04	5.84
Realized Gains Loans [‰]	36906	0.30	0.71	-0.07	0.00	0.05	0.28	5.05
Total Capital Ratio$_{t-1}$ [%]	37300	15.12	4.58	9.00	12.14	13.94	16.60	36.10
Book Leverage$_{t-1}$	41748	11.25	3.19	4.52	9.23	10.93	12.82	23.39
q_{t-1}	38434	1.39	0.72	0.17	0.88	1.30	1.79	3.89
Bank Size$_{t-1}$	41748	20.58	1.48	18.87	19.53	20.19	21.16	25.65

Figure 1: Book Leverage Growth and Total Asset Growth
This scatter plot shows the positive and highly significant relation between ΔTotal Assets and ΔBook Leverage of US commercial and savings banks between Q1-1994 and Q1-2013 (41748 bank-quarter observations). The solid line displays the fitted values from an OLS regression of ΔBook Leverage on ΔTotal Assets. ΔTotal Assets and ΔBook Leverage are defined as $ln[variable_t]$ - $ln[variable_{t-1}]$ and the data is obtained from *SNL Financial*.

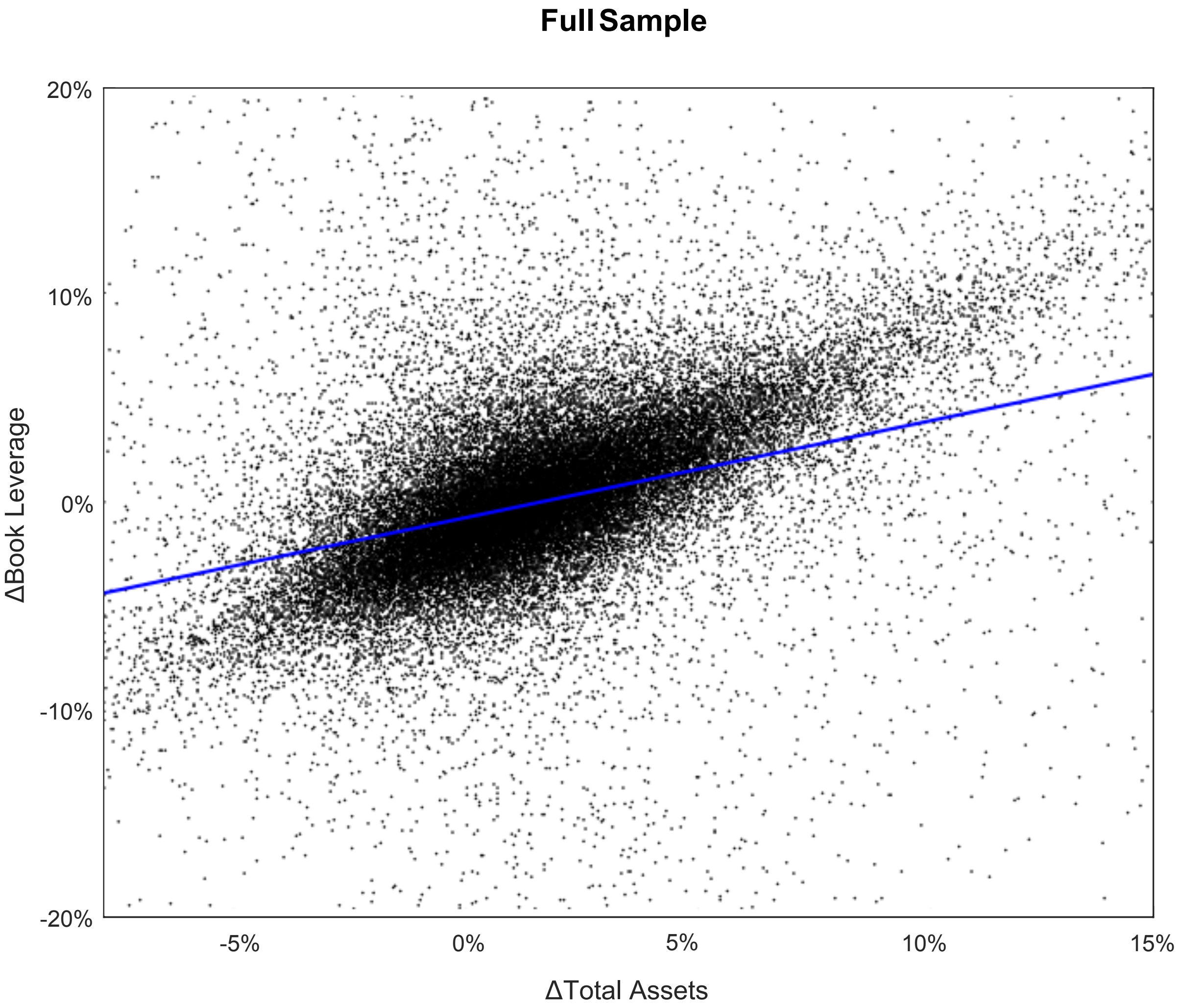

Table 3: Measuring Procyclical Leverage

This table reports the estimation results for regression models (1a) to (2), and variations thereof. The dependent variable is either the quarterly growth rate of book leverage (ΔBook Leverage) or the quarterly growth rate of total assets (ΔTotal Assets). The key explanatory variables are the quarterly growth rates of GDP (ΔGDP), total assets (ΔTotal Assets), and their interaction. Depending on the specification, we distinguish between upswings and downswings. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	ΔBook Leverage						ΔTotal Assets	
ΔTotal Assets	0.510***				0.490***	0.485***		
	(0.020)				(0.020)	(0.023)		
ΔTotal Assets * $1_{\Delta TA>0}$		0.428***						
		(0.024)						
ΔTotal Assets * $1_{\Delta TA<0}$		0.645***						
		(0.060)						
ΔGDP			0.643***		0.545***	0.525***	0.200***	
			(0.059)		(0.056)	(0.065)	(0.038)	
ΔGDP * $1_{\Delta GDP>0}$				1.167***				0.793***
				(0.083)				(0.063)
ΔGDP * $1_{\Delta GDP<0}$				1.229***				-0.651***
				(0.190)				(0.092)
ΔTotal Assets * ΔGDP						0.884		
						(2.081)		
$1_{\Delta TA>0}$		0.007***						
		(0.001)						
$1_{\Delta GDP>0}$				-0.015***				0.001
				(0.002)				(0.001)
Constant	-0.020***	-0.023***	-0.011***	-0.001	-0.021***	-0.021***	0.020***	0.016***
	(0.004)	(0.004)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Observations	41748	41748	41748	41748	41748	41748	41748	41748
R^2	0.176	0.180	0.030	0.033	0.132	0.132	0.076	0.081
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	Yes	Yes	No	No	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 4: Procyclical Leverage, Business Model, and Bank Size

This table reports the estimation results for regression models (3a) and (3b). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The explanatory variables are the quarterly growth rates of total assets (ΔTotal Assets) and real GDP (ΔGDP) as well as lagged bank size (Bank $Size_{t-1}$), a dummy for savings banks ($1_{\text{Savings Banks}}$), a dummy for commercial banks with more than 20% fair value assets ($1_{\text{Commercial Banks>20\% FV}}$), and several interaction terms as discussed in Section 3. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample					
	[1]	[2]	[3]	[4]	[5]	[6]
	ΔBook Leverage					
ΔTotal Assets (TA)	0.490***	0.404***	1.612***	0.462***	0.460***	1.628***
	(0.020)	(0.025)	(0.269)	(0.019)	(0.019)	(0.269)
ΔTA * $1_{\text{Savings Bank}}$		0.163***	0.158***			0.159***
		(0.054)	(0.052)			(0.051)
ΔTA * $1_{\text{Commercial Bank>20\% FV}}$		0.101***	0.129***			0.128***
		(0.038)	(0.039)			(0.039)
ΔTA * Bank $Size_{t-1}$			-0.059***			-0.060***
			(0.013)			(0.013)
ΔGDP	0.545***	0.471***	0.465***	0.461***	-2.118***	-2.404***
	(0.056)	(0.055)	(0.054)	(0.074)	(0.753)	(0.712)
ΔGDP * $1_{\text{Savings Bank}}$				-0.437***	-0.412***	-0.428***
				(0.153)	(0.154)	(0.154)
ΔGDP * $1_{\text{Commercial Bank>20\% FV}}$				0.288**	0.267**	0.250**
				(0.129)	(0.128)	(0.127)
ΔGDP * Bank $Size_{t-1}$					0.125***	0.140***
					(0.036)	(0.034)
Bank $Size_{t-1}$			-0.001**		-0.002***	-0.001***
			(0.000)		(0.000)	(0.000)
$1_{\text{Savings Bank}}$		0.000	0.000	0.005***	0.005***	0.002
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$1_{\text{Commercial Bank>20\% FV}}$		-0.003***	-0.003***	-0.003**	-0.002**	-0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.021***	-0.009***	0.006	-0.010***	0.039***	0.020***
	(0.000)	(0.001)	(0.006)	(0.001)	(0.006)	(0.008)
Observations	41748	41748	41748	41748	41748	41748
R^2	0.132	0.103	0.109	0.102	0.104	0.110
Differences:						
ΔTA * $1_{\text{Savings Bank}}$ – ΔTA * $1_{\text{Commercial Bank>20\% FV}}$		0.062	0.029			0.031
ΔGDP * $1_{\text{Savings Bank}}$ – ΔGDP * $1_{\text{Commercial Bank>20\% FV}}$				-0.725***	-0.679***	-0.678***
Bank Fixed Effects	Yes	No	No	No	No	No
Quarter-Year Fixed Effects	No	No	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank	Bank	Bank

Table 5: Determinants of the Relation between Book Leverage Growth and Total Asset Growth This table reports the estimation results for regression model (4a). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of total assets (ΔTotal Assets) and unrealized gains on AfS securities (Unrealized Gains AfS), net income (Net Income), the lagged total capital ratio (Total Capital Ratio$_{t-1}$), the quarterly growth rate of the average risk weight (ΔRisk Weight), and the lagged book leverage ratio (Book Leverage$_{t-1}$). For each interaction term we distinguish between ΔTotal Assets>0 and ΔTotal Assets<0 to account for potential non-linearities in effects. Variables are defined in Table A1. For expositional purposes we multiply the accounting items with 1000 and ΔRisk Weight as well as Total Capital Ratio$_{t-1}$ with 100. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample [1] ΔBook Leverage	**Savings Banks** [2] ΔBook Leverage	**CB < 20% FV** [3] ΔBook Leverage	**CB > 20% FV** [4] ΔBook Leverage
ΔTotal Assets (TA)	0.719***	1.376***	0.439*	1.136***
	(0.163)	(0.397)	(0.230)	(0.264)
ΔTA * Unrealized Gains AfS * $1_{\Delta TA>0}$	-0.012	-0.020	-0.003	-0.018
	(0.014)	(0.043)	(0.026)	(0.017)
ΔTA * Unrealized Gains AfS * $1_{\Delta TA<0}$	0.044*	0.172*	0.010	0.041
	(0.023)	(0.088)	(0.043)	(0.027)
ΔTA * Net Income * $1_{\Delta TA>0}$	0.052***	-0.000	0.058***	0.028
	(0.014)	(0.047)	(0.016)	(0.023)
ΔTA * Net Income * $1_{\Delta TA<0}$	0.124***	0.069*	0.144***	0.093***
	(0.015)	(0.040)	(0.018)	(0.034)
ΔTA * Total Capital Ratio$_{t-1}$ * $1_{\Delta TA>0}$	0.012**	-0.005	0.020***	0.001
	(0.005)	(0.009)	(0.007)	(0.008)
ΔTA * Total Capital Ratio$_{t-1}$ * $1_{\Delta TA<0}$	0.003	-0.005	0.020	-0.020
	(0.009)	(0.015)	(0.014)	(0.019)
ΔTA * ΔRisk Weight * $1_{\Delta TA>0}$	-0.009*	0.021*	-0.010	-0.015**
	(0.005)	(0.011)	(0.007)	(0.007)
ΔTA * ΔRisk Weight * $1_{\Delta TA<0}$	0.029***	0.023	0.030**	0.028*
	(0.010)	(0.014)	(0.014)	(0.015)
ΔTA * Book Leverage$_{t-1}$ * $1_{\Delta TA>0}$	-0.054***	-0.071**	-0.046***	-0.063***
	(0.009)	(0.030)	(0.013)	(0.016)
ΔTA * Book Leverage$_{t-1}$* $1_{\Delta TA<0}$	0.000	-0.025	0.004	-0.006
	(0.011)	(0.032)	(0.013)	(0.024)
ΔGDP	0.417***	-0.115	0.761***	0.096
	(0.071)	(0.155)	(0.093)	(0.147)
Unrealized Gains AfS	-0.011***	-0.008***	-0.011***	-0.012***
	(0.000)	(0.001)	(0.001)	(0.000)
Net Income	-0.009***	-0.009***	-0.009***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Total Capital Ratio$_{t-1}$	0.000	0.001	-0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)
ΔRisk Weight	0.000	-0.000	-0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Bank Size$_{t-1}$	-0.009***	-0.011	-0.008***	-0.014***
	(0.001)	(0.010)	(0.002)	(0.003)
q_{t-1}	0.003***	-0.001	0.003**	0.002
	(0.001)	(0.003)	(0.001)	(0.002)
Book Leverage$_{t-1}$	-0.004***	-0.004***	-0.005***	-0.005***
	(0.000)	(0.001)	(0.001)	(0.001)
$1_{\Delta TA>0}$	0.007***	0.003	0.007***	0.006***
	(0.001)	(0.002)	(0.002)	(0.002)
ΔGoodwill	-0.225***	-0.261***	-0.260***	-0.163***
	(0.020)	(0.080)	(0.028)	(0.024)
Constant	0.264***	0.315	0.257***	0.390***
	(0.037)	(0.214)	(0.046)	(0.072)
Observations	26034	3537	13487	9010
R^2	0.402	0.442	0.364	0.517
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

Table 6: Determinants of the Relation between Book Leverage Growth and GDP Growth

This table reports the estimation results for regression model (4b). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of GDP (ΔGDP) and unrealized gains on AfS securities (Unrealized Gains AfS), net income (Net Income), the lagged total capital ratio (Total Capital Ratio$_{t-1}$), the quarterly growth rate of the average risk weight (ΔRisk Weight), and the lagged book leverage ratio (Book Leverage$_{t-1}$). For each interaction term we distinguish between ΔGDP>0 and ΔGDP<0 to account for potential non-linearities in effects across up- and downswings. Variables are defined in Table A1. For expositional purposes we multiply the accounting items with 1000 and ΔRisk Weight as well as Total Capital Ratio$_{t-1}$ with 100. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample [1] ΔBook Leverage	Savings Banks [2] ΔBook Leverage	CB < 20% FV [3] ΔBook Leverage	CB > 20% FV [4] ΔBook Leverage
ΔGDP	1.387*	-1.958	2.593**	0.895
	(0.804)	(1.249)	(1.229)	(1.431)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP>0}$	0.006	0.044	0.153	-0.069
	(0.065)	(0.245)	(0.146)	(0.070)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP<0}$	-0.170	-0.153	-0.532***	0.168
	(0.108)	(0.257)	(0.199)	(0.128)
ΔGDP * Net Income * $1_{\Delta GDP>0}$	-0.004	0.174	-0.111	0.090
	(0.058)	(0.143)	(0.078)	(0.123)
ΔGDP * Net Income * $1_{\Delta GDP<0}$	-0.141**	-0.130	-0.130	-0.205
	(0.066)	(0.105)	(0.085)	(0.148)
ΔGDP * Total Capital Ratio$_{t-1}$ * $1_{\Delta GDP>0}$	-0.070***	0.006	-0.097**	-0.060
	(0.025)	(0.029)	(0.046)	(0.042)
ΔGDP * Total Capital Ratio$_{t-1}$ * $1_{\Delta GDP<0}$	-0.153***	-0.001	-0.163**	-0.308***
	(0.033)	(0.036)	(0.070)	(0.074)
ΔGDP * ΔRisk Weight * $1_{\Delta GDP>0}$	0.001	-0.030	-0.023	0.056
	(0.034)	(0.086)	(0.052)	(0.052)
ΔGDP * ΔRisk Weight * $1_{\Delta GDP<0}$	-0.132**	-0.007	-0.183**	-0.040
	(0.059)	(0.127)	(0.085)	(0.094)
ΔGDP * Book Leverage$_{t-1}$* $1_{\Delta GDP>0}$	-0.038	0.148	-0.078	-0.048
	(0.043)	(0.095)	(0.060)	(0.071)
ΔGDP * Book Leverage$_{t-1}$* $1_{\Delta GDP<0}$	0.222***	0.234*	0.163**	0.377***
	(0.060)	(0.120)	(0.080)	(0.119)
ΔTotal Assets	0.602***	0.763***	0.531***	0.665***
	(0.025)	(0.077)	(0.033)	(0.036)
Unrealized Gains AfS	-0.012***	-0.010***	-0.013***	-0.012***
	(0.000)	(0.002)	(0.001)	(0.001)
Net Income	-0.011***	-0.011***	-0.010***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Total Capital Ratio$_{t-1}$	0.001***	0.001	0.001***	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
ΔRisk Weight	-0.001**	0.001	-0.001**	-0.001**
	(0.000)	(0.001)	(0.000)	(0.000)
Bank Size$_{t-1}$	-0.008***	-0.010	-0.007***	-0.013***
	(0.002)	(0.008)	(0.002)	(0.003)
q_{t-1}	0.005***	-0.003	0.006***	0.003**
	(0.001)	(0.004)	(0.001)	(0.002)
Book Leverage$_{t-1}$	-0.004***	-0.006***	-0.005***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
$1_{\Delta GDP>0}$	-0.006***	0.000	-0.008***	-0.002
	(0.002)	(0.004)	(0.002)	(0.003)
ΔGoodwill	-0.263***	-0.290***	-0.308***	-0.193***
	(0.022)	(0.102)	(0.031)	(0.028)
Constant	0.240***	0.318	0.222***	0.388***
	(0.040)	(0.193)	(0.049)	(0.076)
Observations	26034	3537	13487	9010
R^2	0.371	0.414	0.323	0.506
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

Table 7: Asset-Liability-Component Analysis of Procyclical Bank Leverage
This table reports the estimation results for a modified version of regression model (1a). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). In Panel A, the key explanatory variables are the quarterly growth rates of loans (ΔLoans), (AfS and HtM) securities (ΔSecurities), as well as cash & equivalents (ΔCash). In Panel B, the key explanatory variables are the quarterly growth rates of deposits (ΔDeposits), senior debt (ΔSenior Debt) and subordinated debt (ΔSubordinated Debt). For each asset and liability component, we differentiate between balance sheet expansions and contractions by forming interaction terms. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial*. This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

Panel A	**Full Sample** [1] ΔBook Leverage	**Savings Banks** [2] ΔBook Leverage	**CB < 20% FV** [3] ΔBook Leverage	**CB > 20% FV** [4] ΔBook Leverage
ΔLoans * $1_{\Delta TA>0}$	0.209***	0.307***	0.203***	0.184***
	(0.020)	(0.061)	(0.028)	(0.027)
ΔLoans * $1_{\Delta TA<0}$	-0.038	-0.052	-0.050	0.057
	(0.033)	(0.075)	(0.054)	(0.041)
ΔSecurities * $1_{\Delta TA>0}$	0.044***	0.025*	0.024***	0.131***
	(0.005)	(0.013)	(0.006)	(0.013)
ΔSecurities* $1_{\Delta TA<0}$	0.031***	-0.002	0.028***	0.094***
	(0.008)	(0.015)	(0.011)	(0.021)
ΔCash * $1_{\Delta TA>0}$	0.024***	0.016***	0.026***	0.030***
	(0.002)	(0.004)	(0.002)	(0.002)
ΔCash * $1_{\Delta TA<0}$	0.025***	0.027***	0.027***	0.022***
	(0.002)	(0.004)	(0.004)	(0.003)
Observations	40787	6790	20912	13085
R^2	0.160	0.145	0.152	0.297
Other Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	Yes	Yes	Yes	Yes
Clustering Level	Bank	Bank	Bank	Bank

Panel B	**Full Sample** [1] ΔBook Leverage	**Savings Banks** [2] ΔBook Leverage	**CB < 20% FV** [3] ΔBook Leverage	**CB > 20% FV** [4] ΔBook Leverage
ΔDeposits * $1_{\Delta TA>0}$	0.334***	0.396***	0.306***	0.370***
	(0.034)	(0.106)	(0.046)	(0.054)
ΔDeposits * $1_{\Delta TA<0}$	0.501***	0.465***	0.536***	0.491***
	(0.062)	(0.094)	(0.090)	(0.113)
ΔSenior Debt * $1_{\Delta TA>0}$	0.037***	0.064***	0.034***	0.036***
	(0.004)	(0.020)	(0.005)	(0.007)
ΔSenior Debt * $1_{\Delta TA<0}$	0.049***	0.079***	0.051***	0.040***
	(0.007)	(0.020)	(0.009)	(0.012)
ΔSubordinated Debt * $1_{\Delta TA>0}$	0.008	-0.012	0.002	0.033***
	(0.008)	(0.028)	(0.011)	(0.011)
ΔSubordinated Debt * $1_{\Delta TA<0}$	0.058***	0.090	0.060***	0.048***
	(0.013)	(0.056)	(0.019)	(0.017)
Observations	14290	1554	8460	4276
R^2	0.179	0.214	0.176	0.298
Other Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	Yes	Yes	Yes	Yes
Clustering Level	Bank	Bank	Bank	Bank

Table 8: Off-Balance Sheet Obligations, Loan Sales, and Procyclical Bank Leverage This table reports the estimation results for modified versions of regression models (4a) and (4b). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of total assets (ΔTotal Assets) and GDP (ΔGDP) with realized gains from the sale of loans (Realized Gains Loans) and the quarterly growth rates of loan commitments (ΔLoan Commitments) as well as off-balance sheet securitized assets (ΔSec. Assets). For each interaction term, we distinguish between upswings and downswings to account for potential non-linearities in effects. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample					
	[1]	[2]	[3]	[4]	[5]	[6]
	ΔBook Leverage					
ΔTotal Assets (TA)	0.529*** (0.024)	0.566*** (0.028)	0.399*** (0.092)	0.356*** (0.119)	0.547*** (0.021)	0.489*** (0.027)
ΔTA * ΔLoan Commitments * $1_{\Delta TA>0}$		-0.816*** (0.138)				
ΔTA * ΔLoan Commitments * $1_{\Delta TA<0}$		1.463*** (0.378)				
ΔTA * ΔSec. Assets * $1_{\Delta TA>0}$				-0.341 (0.207)		
ΔTA * ΔSec. Assets * $1_{\Delta TA<0}$				0.092 (0.607)		
ΔTA * Realized Gains Loans * $1_{\Delta TA>0}$						0.054*** (0.020)
ΔTA * Realized Gains Loans * $1_{\Delta TA<0}$						0.019 (0.046)
ΔGDP	1.027*** (0.078)	1.302*** (0.092)	1.247*** (0.262)	1.331*** (0.375)	0.779*** (0.066)	1.190*** (0.090)
ΔGDP * ΔLoan Commitments * $1_{\Delta GDP>0}$		0.438 (0.813)				
ΔGDP * ΔLoan Commitments * $1_{\Delta GDP<0}$		-1.879 (1.948)				
ΔGDP * ΔSec. Assets * $1_{\Delta GDP>0}$				-0.893 (1.330)		
ΔGDP * ΔSec. Assets * $1_{\Delta GDP<0}$				-0.440 (2.083)		
ΔGDP * Realized Gains Loans * $1_{\Delta GDP>0}$						-0.090 (0.118)
ΔGDP * Realized Gains Loans * $1_{\Delta GDP<0}$						0.772** (0.303)
ΔLoan Commitments	-0.018*** (0.003)	0.015** (0.008)				
ΔSec. Assets			-0.004 (0.007)	0.012 (0.008)		
Realized Gains Loans					-0.005*** (0.001)	-0.005*** (0.001)
Bank $Size_{t-1}$	0.003** (0.001)	0.004*** (0.001)	-0.002 (0.009)	-0.003 (0.008)	0.002 (0.001)	0.003** (0.001)
q_{t-1}	-0.007*** (0.001)	-0.007*** (0.001)	-0.003 (0.006)	-0.004 (0.006)	-0.009*** (0.001)	-0.009*** (0.001)
Book $Leverage_{t-1}$	-0.003*** (0.001)	-0.003*** (0.001)	-0.004 (0.003)	-0.004 (0.003)	-0.004*** (0.000)	-0.003*** (0.000)
$1_{\Delta TA>0}$		0.004*** (0.001)		0.011* (0.005)		0.006*** (0.001)
$1_{\Delta GDP>0}$		-0.008*** (0.002)		-0.002 (0.006)		-0.012*** (0.001)
ΔGoodwill	-0.282*** (0.024)	-0.263*** (0.023)	-0.264*** (0.061)	-0.254*** (0.060)	-0.272*** (0.026)	-0.262*** (0.025)
Constant	-0.039 (0.033)	-0.059* (0.033)	0.063 (0.218)	0.086 (0.208)	-0.013 (0.030)	-0.027 (0.030)
Observations	23937	23937	1664	1664	32805	32805
R^2	0.180	0.191	0.171	0.185	0.180	0.184
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank	Bank	Bank

Appendix

Table A1: Variable Definitions

This table defines the variables used in our empirical analyses and indicates their data source.

Variable	Data Source	Definition
GDP_t	BEA	Real US gross domestic product at the end of quarter t.
$\Delta\text{GDP}_\text{t}$	BEA	$\ln(\text{GDP}_\text{t}) - \ln(\text{GDP}_\text{t-1})$.
$\text{Total Assets}_\text{i,t}$	SNL Financial	Book value of all assets recognized on the balance sheet of bank i at the end of quarter t.
$\Delta\text{Total Assets}_\text{i,t}$	SNL Financial	$\ln(\text{Total Assets}_\text{i,t}) - \ln(\text{Total Assets}_\text{i,t-1})$.
$\text{Total Equity}_\text{i,t}$	SNL Financial	Book value of bank i's equity at the end of quarter t.
$\Delta\text{Total Equity}_\text{i,t}$	SNL Financial	$\ln(\text{Total Equity}_\text{i,t}) - \ln(\text{Total Equity}_\text{i,t-1})$.
$\text{Total Liabilities}_\text{i,t}$	SNL Financial	$\text{Total Assets}_\text{i,t}$ - $\text{Total Equity}_\text{i,t}$.
$\Delta\text{Total Liabilities}_\text{i,t}$	SNL Financial	$\ln(\text{Total Liabilities}_\text{i,t}) - \ln(\text{Total Liabilities}_\text{i,t-1})$.
$\text{Book Leverage}_\text{i,t}$	SNL Financial	$\text{Total Assets}_\text{i,t}$ / $\text{Total Equity}_\text{i,t}$.
$\Delta\text{Book Leverage}_\text{i,t}$	SNL Financial	$\ln(\text{Book Leverage}_\text{i,t}) - \ln(\text{Book Leverage}_\text{i,t-1})$.
$\mathbb{1}_{\Delta\text{Total Assets(TA)}_\text{i,t}>0}$	SNL Financial	Indicator variable equal to one if $\Delta\text{Total Assets}_\text{i,t}$ is positive, zero otherwise.
$\mathbb{1}_{\Delta\text{GDP}_\text{t}>0}$	SNL Financial	Indicator variable equal to one if $\Delta\text{GDP}_\text{t}$ is positive, zero otherwise.
$\mathbb{1}_{\text{Savings Bank}_\text{i}}$	SNL Financial	Indicator variable equal to one if bank i is a savings bank, zero otherwise.
$\mathbb{1}_{\text{Commercial Bank}>20\%\ \text{FV}_\text{i,t}}$	SNL Financial	Indicator variable equal to one if bank i is a commercial bank with more than 20% fair value assets at the end of quarter t, zero otherwise.
$\text{Unrealized Gains AfS}_\text{i,t}$	SNL Financial	Change in net unrealized gain on AfS securities of bank i during quarter t / $\text{Total Assets}_\text{i,t-1}$.
$\text{Net Income}_\text{i,t}$	SNL Financial	Net income of bank i during quarter t / $\text{Total Assets}_\text{i,t-1}$.
$\text{RWA}_\text{i,t}$	SNL Financial	Total risk-weighted assets of bank i at the end of quarter t.
$\text{Total Capital Ratio}_\text{i,t}$	SNL Financial	Total Tier 1 and Tier 2 capital of bank i at the end of quarter t / $\text{RWA}_\text{i,t}$.
$\text{Risk Weight}_\text{i,t}$	SNL Financial	Total risk-weighted assets of bank i at the end of quarter t / $\text{Total Assets}_\text{i,t}$.
$\Delta\text{Risk Weight}_\text{i,t}$	SNL Financial	$\ln(\text{Risk Weight}_\text{i,t}) - \ln(\text{Risk Weight}_\text{i,t-1})$.
$\text{Bank Size}_\text{i,t}$	SNL Financial	$\ln(\text{Total Assets}_\text{i,t})$.
$\text{q}_\text{i,t}$	SNL Financial	$\text{Market Capitalization}_\text{i,t}$ / $\text{Total Equity}_\text{i,t}$.
$\text{Goodwill}_\text{i,t}$	SNL Financial	Excess of purchase price paid over value of net assets acquired of bank i at the end of quarter t.
$\Delta\text{Goodwill}_\text{i,t}$	SNL Financial	$(\text{Goodwill}_\text{i,t} - \text{Goodwill}_\text{i,t-1}) / \lvert\text{Total Assets}_\text{i,t} - \text{Total Assets}_\text{i,t-1}\rvert$.
$\text{Loans}_\text{i,t}$	SNL Financial	Net loans of bank i at the end of quarter t.
$\Delta\text{Loans}_\text{i,t}$	SNL Financial	$\ln(\text{Loans}_\text{i,t}) - \ln(\text{Loans}_\text{i,t-1})$.
$\text{Securities}_\text{i,t}$	SNL Financial	Sum of available-for-sale, held-to-maturity, and trading securities of bank i at the end of quarter t.
$\Delta\text{Securities}_\text{i,t}$	SNL Financial	$\ln(\text{Securities}_\text{i,t}) - \ln(\text{Securities}_\text{i,t-1})$.
$\text{Cash}_\text{i,t}$	SNL Financial	Cash and equivalents of bank i at the end of quarter t.
$\Delta\text{Cash}_\text{i,t}$	SNL Financial	$\ln(\text{Cash}_\text{i,t}) - \ln(\text{Cash}_\text{i,t-1})$.

$\text{Deposits}_{i,t}$	SNL Financial	Total deposits of bank i at the end of quarter t.
$\Delta\text{Deposits}_{i,t}$	SNL Financial	$\ln(\text{Deposits}_{i,t}) - \ln(\text{Deposits}_{i,t-1})$.
$\text{Senior Debt}_{i,t}$	SNL Financial	Senior debt of bank i at the end of quarter t.
$\Delta\text{Senior Debt}_{i,t}$	SNL Financial	$\ln(\text{Senior Debt}_{i,t}) - \ln(\text{Senior Debt}_{i,t-1})$.
$\text{Subordinated Debt}_{i,t}$	SNL Financial	Subordinated debt of bank i at end of quarter t.
$\Delta\text{Subordinated Debt}_{i,t}$	SNL Financial	$\ln(\text{Subordinated Debt}_{i,t}) - \ln(\text{Subordinated Debt}_{i,t-1})$.
$\text{Loan Commitments}_{i,t}$	SNL Financial	Total unused loan commitments outstanding of bank i at the end of quarter t.
$\Delta\text{Loan Commitments}_{i,t}$	SNL Financial	$\ln(\text{Loan Commitments}_{i,t}) - \ln(\text{Loan Commitments}_{i,t-1})$.
$\text{Securitized Assets}_{i,t}$	SNL Financial	Loans held-off balance sheet for securitization purposes of bank i at end of quarter t.
$\Delta\text{Securitized Assets}_{i,t}$	SNL Financial	$\ln(\text{Securitized Assets}_{i,t}) - \ln(\text{Securitized Assets}_{i,t-1})$.
$\text{Realized Gains Loans}_{i,t}$	SNL Financial	Net gains on the sale of loans of bank i during quarter t / $\text{Total Assets}_{i,t-1}$.
$\text{TARP Injections}_{i,t}$	SNL Financial	TARP preferred equity received by bank i in quarter t / $\text{Total Assets}_{i,t}$.
$\text{TARP\_BANK\_QRT}_{i,t}$	SNL Financial	Indicator variable equal to one if bank i received TARP injections in quarter t.
$\text{Mortgage Exp.}_{i,t}$	SNL Financial	Mortgage loans of bank i at end of quarter t / $\text{Total Assets}_{i,t}$.
$\text{Consumer Loan Exp.}_{i,t}$	SNL Financial	Consumer loans of bank i at end of quarter t / $\text{Total Assets}_{i,t}$.
$\text{Commercial RE Exp.}_{i,t}$	SNL Financial	Commercial real estate loans of bank i at end of quarter t / $\text{Total Assets}_{i,t}$.
$\text{II to Non-II}_{i,t}$	SNL Financial	Interest income / non-interest income of bank i during quarter t.
$\text{Derivative Exp.}_{i,Q4\text{-}2000}$	SNL Financial	Gross notional amount of derivatives of bank i at the end of quarter Q4-2000 / $\text{Total Assets}_{i,Q4\text{-}2000}$.
$\text{AfS Equity Exp.}_{i,Q3\text{-}1998}$	SNL Financial	Amount of AfS equity securities of bank i at the end of quarter Q3-1998 / $\text{Total Assets}_{i,Q3\text{-}1998}$.
$\text{Unrealized Gains AfS Debt}_{i,t}$	SNL Financial	Change in net unrealized gain on AfS debt sec. of bank i during quarter t / $\text{Total Assets}_{i,t-1}$.
$\text{Unrealized Gains AfS Equity}_{i,t}$	SNL Financial	Change in net unrealized gain on AfS equity sec. of bank i during quarter t / $\text{Total Assets}_{i,t-1}$.
$\text{Unrealized Gains CF Hedges}_{i,t}$	SNL Financial	Change in net unrealized gain on cash flow hedges of bank i during quarter t / $\text{Total Assets}_{i,t-1}$.
$\text{Unrealized Gains AfS + CF Hedges}_{i,t}$	SNL Financial	Change in net unrealized gain on AfS sec. and cash flow hedges of bank i during quarter t / $\text{Total Assets}_{i,t-1}$.
$\text{Realized Gains AfS \& HtM}_{i,t}$	SNL Financial	Net gains on the sale of HtM and AfS securities of bank i during quarter t / $\text{Total Assets}_{i,t-1}$.
$\text{Residual Net Income}_{i,t}$	SNL Financial	$\text{Net Income}_{i,t} - \text{Realized Gains AfS \& HtM}_{i,t}$.

Internet Appendix to

Procyclicality of U.S. Bank Leverage

Christian Laux Thomas Rauter

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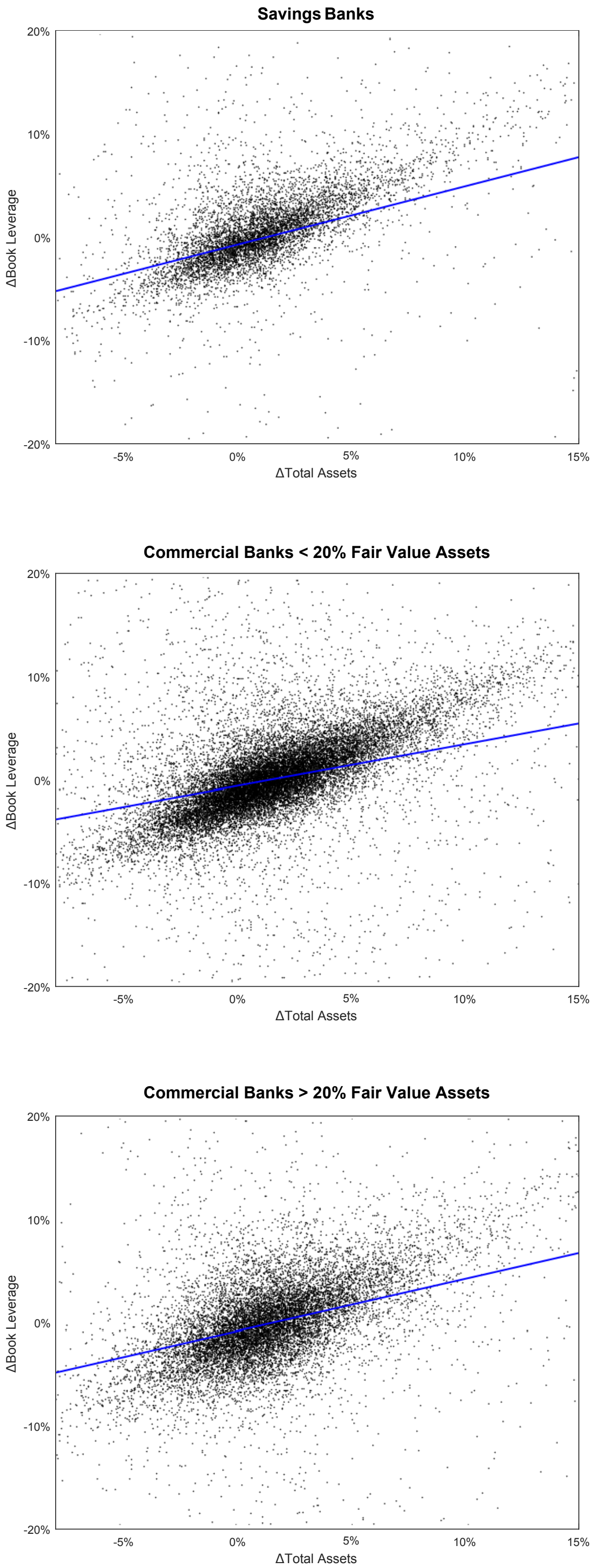
Internet Appendix A: Descriptive Statistics by Bank Type

Table IA1: Summary Statistics by Bank Type
This table reports descriptive statistics for key variables of our empirical analysis by bank type. We report the number of observations (N), mean, standard deviation (SD), 1% quantile, 25% quantile ($Q_{0.25}$), median, 75% quantile ($Q_{0.75}$), and 99% quantile ($Q_{0.99}$). Panels A to C list the descriptive statistics of bank-level variables for savings banks, commercial banks < 20% fair value assets, and commercial banks > 20% fair value assets. The fraction of fair value assets equals the sum of trading assets and AfS securities divided by total assets. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial*. Real GDP is retrieved from the homepage of the *Bureau of Economic Analysis*. This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013.

	N	Mean	SD	$Q_{0.01}$	$Q_{0.25}$	Median	$Q_{0.75}$	$Q_{0.99}$
Panel A: Savings Banks								
ΔTotal Assets [%]	7116	1.50	4.37	-8.17	-0.77	0.91	2.84	22.61
ΔBook Leverage [%]	7116	0.24	7.12	-29.30	-1.85	0.26	2.88	22.25
ΔRisk Weight [%]	4836	0.25	3.65	-11.53	-1.46	0.34	2.01	10.53
ΔGoodwill [%]	6243	0.07	1.86	-5.23	0.00	0.00	0.00	9.39
Unrealized Gains AfS [‰]	6450	0.02	1.31	-5.20	-0.36	0.00	0.45	4.24
Net Income [‰]	7094	1.33	2.15	-9.55	0.80	1.64	2.37	5.49
Realized Gains Loans [‰]	6591	0.39	0.89	-0.07	0.00	0.06	0.33	5.05
Realized Gains AfS & HtM [‰]	7045	0.06	0.41	-1.74	0.00	0.00	0.04	1.74
Residual Net Income [‰]	5943	0.79	2.47	-12.05	0.37	1.25	1.96	4.91
Total Capital Ratio$_{t-1}$ [%]	5421	18.21	6.77	10.08	13.15	16.13	21.34	36.10
Book Leverage$_{t-1}$	7116	10.15	3.54	4.52	7.69	9.83	12.14	21.72
q_{t-1}	6577	1.17	0.61	0.18	0.78	1.07	1.44	3.57
Bank Size$_{t-1}$	7116	20.34	1.21	18.85	19.39	20.06	20.95	23.94
Panel B: Commercial Banks < 20% FV Assets								
ΔTotal Assets [%]	21346	2.05	4.51	-7.97	-0.39	1.49	3.67	23.51
ΔBook Leverage [%]	21346	0.18	6.58	-27.44	-2.23	0.01	2.57	23.92
ΔRisk Weight [%]	16949	0.02	3.28	-11.00	-1.57	0.14	1.73	10.04
ΔGoodwill [%]	20711	0.10	2.58	-12.69	0.00	0.00	0.00	13.89
Unrealized Gains AfS [‰]	18390	0.03	1.01	-3.20	-0.39	0.01	0.49	2.67
Net Income [‰]	21180	1.83	2.50	-10.81	1.29	2.31	3.12	5.85
Realized Gains Loans [‰]	18760	0.32	0.74	-0.07	0.00	0.06	0.30	5.05
Realized Gains AfS & HtM [‰]	21101	0.04	0.33	-1.61	0.00	0.00	0.02	1.41
Residual Net Income [‰]	18076	1.38	2.78	-12.16	0.81	1.99	2.85	5.35
Total Capital Ratio$_{t-1}$ [%]	19369	13.94	3.58	9.00	11.67	13.14	15.08	28.66
Book Leverage$_{t-1}$	21346	11.51	3.10	5.32	9.60	11.11	12.97	23.46
q_{t-1}	19535	1.41	0.73	0.17	0.89	1.33	1.81	3.87
Bank Size$_{t-1}$	21346	20.54	1.46	18.87	19.49	20.13	21.14	25.39
Panel C: Commercial Banks > 20% FV Assets								
ΔTotal Assets [%]	13286	1.79	4.28	-8.09	-0.48	1.28	3.26	20.75
ΔBook Leverage [%]	13286	-0.02	6.06	-20.84	-2.72	-0.27	2.53	21.22
ΔRisk Weight [%]	11183	0.05	3.39	-11.33	-1.69	0.16	1.87	10.45
ΔGoodwill [%]	12867	0.17	2.57	-10.40	0.00	0.00	0.00	14.20
Unrealized Gains AfS [‰]	11627	0.07	2.08	-5.31	-1.07	0.08	1.37	4.65
Net Income [‰]	13205	2.19	1.96	-7.21	1.64	2.47	3.16	5.56
Realized Gains Loans [‰]	11555	0.22	0.52	-0.04	0.00	0.03	0.22	2.75
Realized Gains AfS & HtM [‰]	13172	0.11	0.42	-1.74	0.00	0.00	0.16	1.74
Residual Net Income [‰]	11236	1.86	1.98	-6.91	1.25	2.16	2.91	5.35
Total Capital Ratio$_{t-1}$ [%]	12510	15.60	4.04	9.68	12.83	14.81	17.29	31.00
Book Leverage$_{t-1}$	13286	11.42	3.00	5.62	9.42	11.03	12.86	22.37
q_{t-1}	12322	1.49	0.73	0.18	0.96	1.40	1.89	3.89
Bank Size$_{t-1}$	13286	20.77	1.61	18.88	19.69	20.33	21.31	27.28

Figure IA1: Book Leverage Growth and Total Asset Growth by Bank Type

This scatter plot shows the positive and highly significant relation between ΔTotal Assets and ΔBook Leverage between Q1-1994 and Q1-2013 by bank type (7116 bank-quarter observations for savings banks, 21346 bank-quarter observations for commercial banks < 20% fair value assets, and 13286 bank-quarter observations for commercial banks > 20% fair value assets). The solid lines display the fitted values from OLS regressions of ΔBook Leverage on ΔTotal Assets. The fraction of fair value assets equals the sum of trading assets and AfS securities divided by total assets. ΔTotal Assets and ΔBook Leverage are defined as $ln[variable_t]$ - $ln[variable_{t-1}]$ and the data is obtained from *SNL Financial*.



Internet Appendix B: The Crisis of 2007-2009 and Government Interventions

Table IA2: Changes in Total Assets During the Financial Crisis of 2007-2009

Panel A reports the estimation results for linear regressions of the quarterly growth rate of total assets (ΔTotal Assets) on the quarterly growth rate of GDP (ΔGDP), distinguishing between economic expansions and contractions and focusing on the financial crisis of 2007-2009. In column [2], the interaction term between (ΔGDP) and $1_{\Delta GDP<0}$ only captures quarters during the crisis that had negative GDP growth. In column [3], the interaction captures all other quarters with negative GDP growth. In Panel B, we investigate which assets explain banks' balance sheet expansions in recessionary quarters during the financial crisis. The dependent variable is the quarterly growth rate of total assets (ΔTotal Assets). The key explanatory variables are government sponsored capital injections in the form of TARP (TARP injections) and the quarterly growth rates of deposits (ΔDeposits), loan commitments (ΔLoan Commitments), as well as off-balance sheet securitized assets (ΔSec. Assets). We differentiate between balance sheet expansions and contractions by forming interaction terms. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis*. This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

Panel A	**Full Sample**	**$1_{\Delta GDP<0}$ = only Crisis of 2007-2009**	**$1_{\Delta GDP<0}$ = excl. Crisis of 2007-2009**
	[1]	[2]	[3]
	ΔTotal Assets	ΔTotal Assets	ΔTotal Assets
ΔGDP * $1_{\Delta GDP>0}$	0.793***	0.794***	0.783***
	(0.063)	(0.062)	(0.062)
ΔGDP * $1_{\Delta GDP<0}$	-0.651***	-0.683***	13.741***
	(0.092)	(0.101)	(2.403)
$1_{\Delta GDP>0}$	0.001	0.001	-0.049***
	(0.001)	(0.001)	(0.008)
Constant	0.016***	0.015***	0.067***
	(0.001)	(0.001)	(0.008)
Observations	41748	40098	37791
R^2	0.081	0.084	0.085
Bank Fixed Effects	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No
Clustering Level	Bank	Bank	Bank

Panel B			Crisis of 2007-2009 & ΔGDP<0			
	[1]	[2]	[3]	[4]	[5]	[6]
	ΔTotal Assets	ΔTotal Assets	ΔTotal Assets	ΔTotal Assets	ΔTotal Assets	ΔTotal Assets
TARP Injections * $1_{\Delta TA>0}$		0.473**		0.666***	0.821***	1.287*
		(0.206)		(0.141)	(0.166)	(0.681)
TARP Injections * $1_{\Delta TA<0}$		-0.052		0.090	-0.067	-0.491
		(0.201)		(0.181)	(0.201)	(0.699)
ΔDeposits * $1_{\Delta TA>0}$			0.552***	0.554***	0.572***	0.652***
			(0.024)	(0.025)	(0.037)	(0.089)
ΔDeposits * $1_{\Delta TA<0}$			0.186***	0.189***	0.171***	0.123
			(0.034)	(0.035)	(0.050)	(0.160)
ΔLoan Commitments * $1_{\Delta TA>0}$					0.019*	0.032
					(0.010)	(0.043)
ΔLoan Commitments * $1_{\Delta TA<0}$					0.023**	0.034
					(0.010)	(0.090)
ΔSec. Assets * $1_{\Delta TA>0}$						0.004
						(0.020)
ΔSec. Assets * $1_{\Delta TA<0}$						-0.003
						(0.008)
$1_{\Delta Total\ Assets\ (TA)>0}$		0.055***	0.033***	0.031***	0.029***	0.033***
		(0.002)	(0.001)	(0.002)	(0.002)	(0.008)
Constant	0.015***	-0.023***	-0.011***	-0.010***	-0.009***	-0.029***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.009)
Observations	3957	3648	3951	3642	1808	166
R^2	0.293	0.534	0.767	0.767	0.772	0.811
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustering Level	Bank	Bank	Bank	Bank	Bank	Bank

Table IA3: Relation between Book Leverage Growth and GDP Growth During the Financial Crisis of 2007-2009 This table reports the estimation results for a modified version of regression model (1b) focusing on the financial crisis of 2007-2009. The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The explanatory variables are the quarterly growth rate of GDP(ΔGDP), an indicator variable which is equal to one if bank i received TARP injections in quarter t ($\mathbb{1}_{\text{TARP\_BANK\_QRT}}$), and their interaction. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis*. This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Crisis of 2007-2009 & ΔGDP<0	
	[1]	[2]
	ΔBook Leverage	ΔBook Leverage
ΔGDP	1.755***	-0.395**
	(0.230)	(0.196)
ΔGDP * $1_{\text{TARP\_BANK\_QRT}}$		9.611***
		(0.678)
$1_{\text{TARP\_BANK\_QRT}}$		-0.003
		(0.009)
Constant	0.008***	-0.013***
	(0.002)	(0.002)
Observations	3957	3957
R^2	0.190	0.384
Bank Fixed Effects	Yes	Yes
Quarter-Year Fixed Effects	No	No
Clustering Level	Bank	Bank

Table IA4: Book Leverage Growth and GDP Growth - The Role of Recessions and Government Interventions This table reports the estimation results for a modified version of regression model (4b). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of GDP (ΔGDP) and unrealized gains on AfS securities (Unrealized Gains AfS), net income (Net Income), the lagged total capital ratio (Total Capital Ratio$_{t-1}$), the quarterly growth rate of the average risk weight (ΔRisk Weight), and the lagged book leverage ratio (Book Leverage$_{t-1}$). For each interaction term, we distinguish between ΔGDP>0 and ΔGDP<0 to account for potential non-linearities in effects across up- and downswings. During downswings, we additionally distinguish between (i) bank-quarters in which the leverage of TARP banks was affected by direct government interventions and (ii) all other bank-quarters. Variables are defined in Table A1. For expositional purposes we multiply the accounting items with 1000 and ΔRisk Weight as well as Total Capital Ratio$_{t-1}$ with 100. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis*. This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample [1] ΔBook Leverage	**Savings Banks** [2] ΔBook Leverage	**CB < 20% FV** [3]* ΔBook Leverage	**CB > 20% FV** [4] ΔBook Leverage
ΔGDP	1.210**	-1.724	1.754*	0.644
	(0.578)	(1.056)	(0.929)	(0.931)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP>0}$	-0.007	0.063	0.074	-0.057
	(0.063)	(0.240)	(0.142)	(0.070)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP<0}$	-0.026	-0.212	-0.212*	0.097
	(0.069)	(0.163)	(0.121)	(0.081)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP<0}$ * $1_{TARP\_BANK\_QRT}$	-0.309*	1.550**	-0.526**	0.215
	(0.187)	(0.636)	(0.247)	(0.228)
ΔGDP * Net Income * $1_{\Delta GDP>0}$	0.022	0.176	-0.066	0.082
	(0.058)	(0.141)	(0.078)	(0.120)
ΔGDP * Net Income * $1_{\Delta GDP<0}$	0.009	-0.174*	-0.006	0.156
	(0.057)	(0.090)	(0.078)	(0.114)
ΔGDP * Net Income * $1_{\Delta GDP<0}$ * $1_{TARP\_BANK\_QRT}$	-0.004	1.313	0.047	-0.071
	(0.098)	(0.866)	(0.124)	(0.158)
ΔGDP * Total Capital Ratio$_{t-1}$ * $1_{\Delta GDP>0}$	-0.069***	-0.005	-0.072**	-0.055**
	(0.018)	(0.021)	(0.036)	(0.027)
ΔGDP * Total Capital Ratio$_{t-1}$ * $1_{\Delta GDP<0}$	-0.087***	0.034	-0.087	-0.181***
	(0.024)	(0.030)	(0.059)	(0.057)
ΔGDP * Total Capital Ratio$_{t-1}$ * $1_{\Delta GDP<0}$ * $1_{TARP\_BANK\_QRT}$	-0.518***	-0.126	-0.629***	-0.557***
	(0.076)	(0.402)	(0.106)	(0.147)
ΔGDP * ΔRWA * $1_{\Delta GDP>0}$	-0.017	-0.037	-0.065	0.060
	(0.034)	(0.083)	(0.051)	(0.051)
ΔGDP * ΔRWA * $1_{\Delta GDP<0}$	0.004	0.007	0.049	-0.064
	(0.048)	(0.085)	(0.070)	(0.071)
ΔGDP * ΔRWA * $1_{\Delta GDP<0}$ * $1_{TARP\_BANK\_QRT}$	-0.070	1.039***	-0.084	0.024
	(0.071)	(0.282)	(0.098)	(0.122)
ΔGDP * Book Leverage$_{t-1}$ * $1_{\Delta GDP>0}$	-0.022	0.148	-0.033	-0.028
	(0.034)	(0.090)	(0.051)	(0.053)
ΔGDP * Book Leverage$_{t-1}$ * $1_{\Delta GDP<0}$	-0.023	0.074	-0.050	0.083
	(0.043)	(0.078)	(0.051)	(0.096)
ΔGDP * Book Leverage$_{t-1}$ * $1_{\Delta GDP<0}$ * $1_{TARP\_BANK\_QRT}$	1.151***	0.918***	1.275***	1.078***
	(0.076)	(0.295)	(0.116)	(0.125)
Observations	26034	3537	13487	9010
R^2	0.428	0.440	0.398	0.542
Other Controls and Stand-Alone Variables	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

*As we discuss in Section 6.1, the negative and significant interaction term for commercial banks with less than 20% fair value assets that did not receive TARP funds is driven by large unrealized gains on AfS securities in 2009, which resulted from a decrease in interest rates (see also Xie (2016)).

Internet Appendix C: Alternative Measures of Banks' Business Model

Table IA5: Alternative Measures of Banks' Business Model - Loan Portfolio Decomposition

This table reports the estimation results for extended versions of regression models (3a) and (3b). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of total assets (ΔTotal Assets) and GDP (ΔGDP) with banks' lagged mortgage exposure (Mortgage Exp.$_{t\text{-}1}$), consumer loan exposure (Consumer Loan Exp.$_{t\text{-}1}$), and commercial real estate exposure (Commercial RE Exp.$_{t\text{-}1}$) as well as the fraction of interest to non-interest income (II to Non-II$_{t\text{-}1}$). Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** $<$ 0.01, ** $<$ 0.05, * $<$ 0.10.

	Full Sample							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	ΔBook Leverage							
ΔTotal Assets (TA)	2.549***	2.488***	1.966***	1.982***	2.094***	2.516***	1.659***	1.614***
	(0.493)	(0.501)	(0.321)	(0.321)	(0.512)	(0.493)	(0.275)	(0.277)
ΔTA * Mortgage Exp.$_{t\text{-}1}$		0.272						
		(0.225)						
ΔTA * Consumer Loan Exp.$_{t\text{-}1}$				0.201				
				(0.340)				
ΔTA * Commercial RE Exp.$_{t\text{-}1}$						-0.779***		
						(0.297)		
ΔTA * II to Non-II$_{t\text{-}1}$								0.002
								(0.003)
ΔTA * $1_{\text{Savings Bank}}$	0.225***	0.178**	0.219***	0.220***	0.191***	0.113	0.158***	0.155***
	(0.070)	(0.082)	(0.058)	(0.059)	(0.073)	(0.081)	(0.052)	(0.052)
ΔTA * $1_{\text{Commercial Bank>20\% FV}}$	0.136*	0.140*	0.121**	0.122**	0.137*	0.085	0.127***	0.129***
	(0.073)	(0.072)	(0.051)	(0.051)	(0.070)	(0.072)	(0.039)	(0.039)
ΔTA * Bank Size$_{t\text{-}1}$	-0.106***	-0.105***	-0.077***	-0.079***	-0.084***	-0.095***	-0.061***	-0.059***
	(0.024)	(0.024)	(0.016)	(0.016)	(0.025)	(0.024)	(0.014)	(0.014)
ΔGDP	-1.387	-1.283	-1.952**	-1.993**	-1.532	-1.706	-2.506***	-2.332***
	(1.578)	(1.617)	(0.992)	(0.987)	(1.499)	(1.531)	(0.724)	(0.752)
ΔGDP * Mortgage Exp.$_{t\text{-}1}$		-0.222						
		(0.827)						
ΔGDP * Consumer Loan Exp.$_{t\text{-}1}$				-0.698				
				(1.206)				
ΔGDP * Commercial RE Exp.$_{t\text{-}1}$						0.638		
						(1.002)		
ΔGDP * II to Non-II$_{t\text{-}1}$								-0.008
								(0.010)
ΔGDP * $1_{\text{Savings Bank}}$	-0.069	-0.033	-0.342*	-0.343*	-0.316	-0.270	-0.437***	-0.428***
	(0.234)	(0.283)	(0.189)	(0.189)	(0.230)	(0.246)	(0.154)	(0.155)
ΔGDP * $1_{\text{Commercial Bank>20\% FV}}$	0.462*	0.461*	0.228	0.228	0.405*	0.461*	0.227*	0.217*
	(0.244)	(0.243)	(0.178)	(0.178)	(0.230)	(0.242)	(0.128)	(0.129)
ΔGDP * Bank Size$_{t\text{-}1}$	0.088	0.085	0.121**	0.126***	0.099	0.100	0.145***	0.139***
	(0.078)	(0.078)	(0.048)	(0.048)	(0.074)	(0.074)	(0.035)	(0.036)
Observations	16567	16567	28152	28152	17278	17278	41322	41322
R^2	0.092	0.093	0.091	0.092	0.090	0.092	0.110	0.110
Other Stand-Alone Variables and Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	No	No	No	No	No
Quarter-Year Fixed Effects	No	No	No	No	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Internet Appendix D: Derivatives and AfS Equity Securities

We investigate whether there is a significant increase in procyclical leverage around the introduction of FAS 133 and the change in the regulatory treatment of AfS equity securities. We define an indicator variable that equals 1 for post-change quarters and interact this dummy with ΔTotal Assets and ΔGDP respectively. We use a balanced panel of banks for the time around the introduction of FAS 133 and the partial removal of the prudential filter for AfS equity securities to ensure that the coefficients of the interaction terms are not biased by the entry and exit of banks into/out of our sample. Any observable or unobservable event that influences procyclicality and coincides with the two institutional changes would also bias the coefficients of our estimates. To more cleanly identify effects, we multiply the two interaction terms with the bank's exposure to derivatives (notional) and AfS equity securities right before the institutional change. If the institutional change is associated with more procyclicality, the treatment effects should be positive for banks with larger derivative or AfS equity portfolios.

We do not find any significant increase in procyclical leverage after the introduction of FAS 133 for banks with higher derivative exposure. While the interactions with ΔTotal Assets are insignificant, the interactions with ΔGDP are even negative. These results are robust to using different time windows around the event (Table IA6).

Similarly, the association between total asset growth and book leverage growth is not significantly stronger after the partial removal of the prudential filter for AfS equity securities for banks with large exposures in these assets (Table IA7). In contrast, we find a statistically significant increase in the relation between ΔGDP and ΔBook Leverage after the change in regulatory treatment. However, looking at the effect of unrealized gains and losses on AfS equity securities directly does not support the conclusion that these gains magnify procyclical leverage.

In particular, we split total unrealized gains and losses on AfS securities into their debt and equity components and rerun regression models (4a) and (4b) to examine the role of AfS equity securities for procyclical leverage.[21]

We find a positive and weakly significant interaction term for unrealized gains and losses on AfS equity securities upon balance sheet expansions, but the coefficient becomes insignificant if we exclude the financial crisis of 2007-2009 (Table IA8). As we show in Section 6.1, total assets increased because of TARP in the crisis, which resulted in a decrease of leverage. Since unrealized gains and losses on AfS equity securities became negative at the same time, the interaction term is positive during the crisis period. The coefficient for balance sheet contractions and the interactions of ΔTotal Assets with unrealized gains and losses on AfS debt securities are insignificant. Including unrealized gains and losses on cash flow hedges does not affect our results. The corresponding interaction terms are not significant. Finally, none of the interactions with ΔGDP are significantly different from zero (Table IA9).

[21]The sample period for this test starts at the end of 1998 since the Fed only required banks to report unrealized gains on AfS equity securities after the change in regulatory treatment of these securities.

Table IA6: FAS 133 and Procyclical Leverage

In this table we test whether the introduction of fair value accounting for hedging derivatives via FAS 133 is associated with a significant increase in leverage procyclicality. The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The dummy variable $1_{\text{Year} \geq 2001}$ equals one for quarters after the effective date of FAS 133 at the beginning of 2001 and Deriv.Exp.$_{\text{Q4-2000}}$ captures a bank's gross notional derivative exposure (fraction of total assets) at the end of Q4-2000. The key explanatory variables are the interaction terms between $1_{\text{Year} \geq 2001}$, Deriv.Exp.$_{\text{Q4-2000}}$ and ΔTotal Assets / ΔGDP, which capture the changes in leverage procyclicality for banks with higher derivative exposure after the introduction of FAS 133. This sample covers a balanced panel of US commercial and savings banks around the change in accounting rules for derivatives. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	1999-2002	**Q1-1996 ≤ Pre ≤ Q2-1998 Q1-2001 ≤ Post ≤ Q4-2002**	**1999-2002**	**Q1-1996 ≤ Pre ≤ Q2-1998 Q1-2001 ≤ Post ≤ Q4-2002**
	[1]	[2]	[3]	[4]
	ΔBook Leverage	ΔBook Leverage	ΔBook Leverage	ΔBook Leverage
ΔTotal Assets * Deriv. Exp.$_{\text{Q4-2000}}$ * $1_{\text{Year≥2001}}$			0.096	0.082
			(0.105)	(0.066)
ΔGDP * Deriv. Exp.$_{\text{Q4-2000}}$ * $1_{\text{Year≥2001}}$			-0.824	-0.958***
			(0.715)	(0.322)
ΔTotal Assets * $1_{\text{Year≥2001}}$	0.035	0.140	-0.118	0.043
	(0.075)	(0.105)	(0.090)	(0.127)
ΔGDP * $1_{\text{Year≥2001}}$	-0.184	1.225***	-0.032	1.774***
	(0.265)	(0.365)	(0.290)	(0.402)
ΔTotal Assets	0.699***	0.604***	0.745***	0.611***
	(0.069)	(0.064)	(0.074)	(0.067)
ΔGDP	1.021***	-0.353	1.108***	-0.608**
	(0.127)	(0.246)	(0.136)	(0.264)
$1_{\text{Year≥2001}}$	-0.004	-0.005	-0.002	-0.013***
	(0.002)	(0.005)	(0.002)	(0.004)
Deriv. Exp.$_{\text{Q4-2000}}$			0.007*	0.013***
			(0.004)	(0.003)
Constant	0.336	0.150	0.015	0.011
	(0.295)	(0.149)	(0.017)	(0.015)
Observations	3673	3009	2742	2292
R^2	0.458	0.459	0.338	0.333
Other Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	No	No
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

Table IA7: Changes in Regulatory Treatment of Unrealized AfS Equity Gains and Procyclical Leverage In this table we test whether the partial removal of the prudential filter for unrealized gains on AfS equity securities in Q4-1998 is associated with a significant increase in leverage procyclicality. The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The dummy variable $1_{\text{Quarter} \geq \text{Q4-1998}}$ equals one for quarters after the effective date of the regulatory change at the beginning of Q4-1998 and AfS. Equity Exp.$_{\text{Q3-1998}}$ captures a bank's exposure to AfS equity securities (fraction of total assets) at the end of Q3-1998. The key explanatory variables are the interaction terms between $1_{\text{Quarter} \geq \text{Q4-1998}}$, AfS. Equity Exp.$_{\text{Q3-1998}}$ and ΔTotal Assets / ΔGDP, which capture the changes in leverage procyclicality for banks with higher AfS equity exposure after the partial removal of the prudential filter in Q4-1998. This sample covers a balanced panel of US commercial and savings banks around the regulatory change. Variables are defined in Table A1. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Q1-1997 to Q4-2000	Q1-1994 to Q4-2000	Q1-1997 to Q4-2000	Q1-1994 to Q4-2000
	[1]	[2]	[3]	[4]
	ΔBook Leverage	ΔBook Leverage	ΔBook Leverage	ΔBook Leverage
ΔTotal Assets * AfS Equity Exp.$_{\text{Q3-1998}}$ * $1_{\text{Quarter}\geq\text{Q4-1998}}$			-16.963	-13.977
			(11.157)	(8.666)
ΔGDP * AfS Equity Exp.$_{\text{Q3-1998}}$ * $1_{\text{Quarter}\geq\text{Q4-1998}}$			62.014**	73.972***
			(29.904)	(23.982)
ΔTotal Assets * $1_{\text{Quarter}\geq\text{Q4-1998}}$	0.083	0.077	0.295**	0.188
	(0.089)	(0.093)	(0.135)	(0.131)
ΔGDP * $1_{\text{Quarter}\geq\text{Q4-1998}}$	1.905***	0.266	1.463*	-0.358
	(0.542)	(0.350)	(0.747)	(0.359)
ΔTotal Assets	0.659***	0.666***	0.634***	0.693***
	(0.081)	(0.069)	(0.087)	(0.062)
ΔGDP	-0.897*	0.923***	-0.894	1.037***
	(0.537)	(0.275)	(0.639)	(0.260)
$1_{\text{Quarter}\geq\text{Q4-1998}}$	-0.007	0.008	-0.014*	0.005
	(0.007)	(0.007)	(0.008)	(0.004)
AfS Equity Exp.$_{\text{Q3-1998}}$			0.203	0.136
			(0.295)	(0.228)
Constant	-0.254	0.128	0.011	0.002
	(0.346)	(0.242)	(0.019)	(0.016)
Observations	2330	2256	1854	1936
R^2	0.444	0.415	0.345	0.408
Other Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	No	No
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

Table IA8: Determinants of the Relation between Book Leverage Growth and Total Asset Growth - Supplementary Tests on the Role of Fair Value Accounting This table reports the estimation results for a modified version of regression model (4a). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of total assets (ΔTotal Assets) and unrealized gains on AfS securities (Unrealized Gains AfS), unrealized gains on AfS debt securities (Unrealized Gains AfS Debt), unrealized gains on AfS equity securities (Unrealized Gains AfS Equity), unrealized gains on cash flow hedges (Unrealized Gains CF Hedges), and the sum of unrealized gains on AfS securities and cash flow hedges (Unrealized Gains AfS + CF Hedges). For each interaction term we distinguish between ΔTotal Assets>0 and ΔTotal Assets<0 to account for potential non-linearities in effects. Variables are defined in Table A1. For expositional purposes we multiply the accounting items with 1000. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample			
	[1]	[2]*	[3]	[4]
	ΔBook Leverage			
ΔTotal Assets (TA)	0.719***	0.575***	0.716***	0.720***
	(0.163)	(0.197)	(0.163)	(0.163)
ΔTA * Unrealized Gains AfS * $1_{\Delta TA>0}$	-0.012			-0.011
	(0.014)			(0.014)
ΔTA * Unrealized Gains AfS * $1_{\Delta TA<0}$	0.044*			0.045*
	(0.023)			(0.023)
ΔTA * Unrealized Gains AfS Debt * $1_{\Delta TA>0}$		-0.005		
		(0.015)		
ΔTA * Unrealized Gains AfS Debt * $1_{\Delta TA<0}$		0.024		
		(0.024)		
ΔTA * Unrealized Gains AfS Equity * $1_{\Delta TA>0}$		0.550*		
		(0.324)		
ΔTA * Unrealized Gains AfS Equity * $1_{\Delta TA<0}$		-0.105		
		(0.616)		
ΔTA * Unrealized Gains AfS + CF Hedges * $1_{\Delta TA>0}$			-0.010	
			(0.014)	
ΔTA * Unrealized Gains AfS + CF Hedges * $1_{\Delta TA<0}$			0.042*	
			(0.023)	
ΔTA * Unrealized Gains CF Hedges * $1_{\Delta TA>0}$				0.449
				(0.308)
ΔTA * Unrealized Gains CF Hedges * $1_{\Delta TA<0}$				-0.489
				(0.549)
ΔGDP	0.417***	0.654***	0.413***	0.416***
	(0.071)	(0.083)	(0.071)	(0.072)
Unrealized Gains AfS	-0.011***			-0.011***
	(0.000)			(0.000)
Unrealized Gains AfS Debt		-0.011***		
		(0.000)		
Unrealized Gains AfS Equity		-0.033***		
		(0.008)		
Unrealized Gains AfS + CF Hedges			-0.011***	
			(0.000)	
Unrealized Gains CF Hedges				-0.021***
				(0.008)
Observations	26034	17796	25931	25931
R^2	0.402	0.407	0.403	0.403
Other Controls and Interactions	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

*As we discuss in Section 6.3, the positive and weakly significant interaction term for unrealized gains and losses on AfS equity securities upon balance sheet expansions becomes insignificant if we exclude the financial crisis of 2007-2009.

Table IA9: Determinants of the Relation between Book Leverage Growth and GDP Growth - Supplementary Tests on the Role of Fair Value Accounting This table reports the estimation results for a modified version of regression model (4b). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of GDP (ΔGDP) and unrealized gains on AfS securities (Unrealized Gains AfS), unrealized gains on AfS debt securities (Unrealized Gains AfS Debt), unrealized gains on AfS equity securities (Unrealized Gains AfS Equity), unrealized gains on cash flow hedges (Unrealized Gains CF Hedges), and the sum of unrealized gains on AfS securities and cash flow hedges (Unrealized Gains AfS + CF Hedges). For each interaction term we distinguish between ΔGDP>0 and ΔGDP<0 to account for potential non-linearities in effects. Variables are defined in Table A1. For expositional purposes we multiply the accounting items with 1000. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample			
	[1]	[2]	[3]	[4]
	ΔBook Leverage			
ΔGDP	1.387*	4.115***	1.299	1.322*
	(0.804)	(1.080)	(0.798)	(0.800)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP>0}$	0.006			0.007
	(0.065)			(0.065)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP<0}$	-0.170			-0.180
	(0.108)			(0.109)
ΔGDP * Unrealized Gains AfS Debt * $1_{\Delta GDP>0}$		0.084		
		(0.074)		
ΔGDP * Unrealized Gains AfS Debt * $1_{\Delta GDP<0}$		-0.210		
		(0.145)		
ΔGDP * Unrealized Gains AfS Equity * $1_{\Delta GDP>0}$		0.832		
		(1.212)		
ΔGDP * Unrealized Gains AfS Equity * $1_{\Delta GDP<0}$		-3.359		
		(4.243)		
ΔGDP * Unrealized Gains AfS + CF Hedges * $1_{\Delta GDP>0}$			-0.006	
			(0.065)	
ΔGDP * Unrealized Gains AfS + CF Hedges * $1_{\Delta GDP<0}$			-0.139	
			(0.107)	
ΔGDP * Unrealized Gains CF Hedges * $1_{\Delta GDP>0}$				-0.728
				(1.264)
ΔGDP * Unrealized Gains CF Hedges * $1_{\Delta GDP<0}$				2.061
				(2.512)
ΔTotal Assets	0.602***	0.553***	0.601***	0.602***
	(0.025)	(0.029)	(0.025)	(0.025)
Unrealized Gains AfS	-0.012***			-0.012***
	(0.000)			(0.000)
Unrealized Gains AfS Debt		-0.013***		
		(0.001)		
Unrealized Gains AfS Equity		-0.028**		
		(0.013)		
Unrealized Gains AfS + CF Hedges			-0.012***	
			(0.000)	
Unrealized Gains CF Hedges				-0.003
				(0.011)
Observations	26034	17796	25931	25931
R^2	0.371	0.376	0.371	0.372
Other Controls and Interactions	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

Internet Appendix E: Additional Tests

Table IA10: Book Leverage Dynamics of US Non-Financial Firms versus Banks
This table compares the book leverage dynamics of US non-financial firms and banks. We report the coefficient estimates from linear regressions of the quarterly growth rate of book leverage (ΔBook Leverage) on the quarterly growth rate of total assets (ΔTotal Assets) and/or GDP (ΔGDP). Variables are defined in Table A1. Firm and bank fundamentals are obtained from *Compustat* and *SNL Financial*, respectively. Real GDP is retrieved from the homepage of the *Bureau of Economic Analysis*. This sample covers the time period Q1-1994 to Q1-2013. Clustered standard errors at the firm or bank level are given in parentheses. Significance is indicated by: *** $<$ 0.01, ** $<$ 0.05, * $<$ 0.10.

	Non-Financial Firms			**Banks**		
	[1]	[2]	[3]	[4]	[5]	[6]
	ΔBook Leverage			ΔBook Leverage		
ΔTotal Assets	0.171***		0.172***	0.463***		0.461***
	(0.014)		(0.014)	(0.019)		(0.019)
ΔGDP		-0.118	-0.275**		0.547***	0.463***
		(0.112)	(0.112)		(0.057)	(0.055)
Constant	-0.002**	0.003***	-0.001	-0.007***	-0.001***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Observations	49686	49686	49686	41748	41748	41748
R^2	0.017	0.000	0.017	0.099	0.003	0.101
Bank Fixed Effects	No	No	No	No	No	No
Quarter-Year Fixed Effects	No	No	No	No	No	No
Clustering Level	Firm	Firm	Firm	Bank	Bank	Bank

Table IA11: Determinants of the Relation between Book Leverage Growth and Total Asset Growth - Explicitly Controlling for Realized Gains This table reports the estimation results for a modified version of regression model (4a). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of total assets (ΔTotal Assets) and unrealized gains on AfS securities (Unrealized Gains AfS), realized gains on AfS and HtM securities (Realized Gains AfS & HtM), residual net income (Residual Net Income), the lagged total capital ratio (Total Capital Ratio$_{t-1}$), the quarterly growth rate of the average risk weight (ΔRisk Weight), and the lagged book leverage ratio (Book Leverage$_{t-1}$). For each interaction term we distinguish between ΔTotal Assets>0 and ΔTotal Assets<0 to account for potential non-linearities in effects. Variables are defined in Table A1. For expositional purposes we multiply the accounting items with 1000 and ΔRisk Weight as well as Total Capital Ratio$_{t-1}$ with 100. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample [1] ΔBook Leverage	**Savings Banks** [2] ΔBook Leverage	**CB < 20% FV** [3] ΔBook Leverage	**CB > 20% FV** [4] ΔBook Leverage
ΔTotal Assets (TA)	0.700***	1.315***	0.432*	1.169***
	(0.165)	(0.372)	(0.235)	(0.268)
ΔTA * Unrealized Gains AfS * $1_{\Delta TA>0}$	-0.012	-0.016	0.000	-0.019
	(0.014)	(0.046)	(0.026)	(0.018)
ΔTA * Unrealized Gains AfS * $1_{\Delta TA<0}$	0.033	0.143*	-0.036	0.044
	(0.026)	(0.080)	(0.044)	(0.033)
ΔTA * Realized Gains AfS & HtM * $1_{\Delta TA>0}$	0.086	-0.254*	0.154**	0.071
	(0.056)	(0.140)	(0.075)	(0.083)
ΔTA * Realized Gains AfS & HtM * $1_{\Delta TA<0}$	0.014	-0.021	-0.060	0.015
	(0.084)	(0.214)	(0.098)	(0.151)
ΔTA * Residual Net Income * $1_{\Delta TA>0}$	0.049***	-0.003	0.056***	0.015
	(0.015)	(0.049)	(0.018)	(0.021)
ΔTA * Residual Net Income * $1_{\Delta TA<0}$	0.136***	0.094**	0.160***	0.093**
	(0.016)	(0.039)	(0.018)	(0.037)
ΔTA * Total Capital Ratio$_{t-1}$ * $1_{\Delta TA>0}$	0.013***	-0.005	0.021***	0.002
	(0.005)	(0.009)	(0.007)	(0.008)
ΔTA * Total Capital Ratio$_{t-1}$ * $1_{\Delta TA<0}$	0.003	-0.001	0.016	-0.021
	(0.009)	(0.015)	(0.015)	(0.018)
ΔTA * ΔRisk Weight * $1_{\Delta TA>0}$	-0.009**	0.025**	-0.010	-0.016***
	(0.005)	(0.013)	(0.007)	(0.006)
ΔTA * ΔRisk Weight * $1_{\Delta TA<0}$	0.030***	0.021	0.029**	0.030**
	(0.010)	(0.014)	(0.014)	(0.015)
ΔTA * Book Leverage$_{t-1}$ * $1_{\Delta TA>0}$	-0.053***	-0.062**	-0.046***	-0.064***
	(0.010)	(0.027)	(0.013)	(0.016)
ΔTA * Book Leverage$_{t-1}$* $1_{\Delta TA<0}$	-0.000	-0.025	0.006	-0.009
	(0.012)	(0.032)	(0.013)	(0.026)
ΔGDP	0.407***	-0.123	0.750***	0.088
	(0.071)	(0.154)	(0.094)	(0.143)
Unrealized Gains AfS	-0.011***	-0.008***	-0.011***	-0.011***
	(0.000)	(0.001)	(0.001)	(0.000)
Realized Gains AfS & HtM	-0.017***	-0.013**	-0.019***	-0.016***
	(0.002)	(0.006)	(0.003)	(0.002)
Residual Net Income	-0.009***	-0.008***	-0.009***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Total Capital Ratio$_{t-1}$	0.000	0.001	-0.000	-0.001**
	(0.000)	(0.001)	(0.000)	(0.000)
ΔRisk Weight	0.000	-0.000	-0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.000)
Bank Size$_{t-1}$	-0.009***	-0.011	-0.008***	-0.013***
	(0.001)	(0.010)	(0.002)	(0.003)
q_{t-1}	0.002**	-0.001	0.002*	0.003*
	(0.001)	(0.003)	(0.001)	(0.002)
Book Leverage$_{t-1}$	-0.004***	-0.004***	-0.005***	-0.005***
	(0.000)	(0.001)	(0.001)	(0.001)
$1_{\Delta TA>0}$	0.007***	0.002	0.007***	0.006***
	(0.001)	(0.002)	(0.002)	(0.002)
ΔGoodwill	-0.227***	-0.254***	-0.259***	-0.166***
	(0.020)	(0.072)	(0.029)	(0.025)
Constant	0.261***	0.306	0.262***	0.378***
	(0.038)	(0.215)	(0.045)	(0.072)
Observations	25889	3521	13405	8963
R^2	0.396	0.435	0.360	0.512
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

Table IA12: Determinants of the Relation between Book Leverage Growth and GDP Growth - Explicitly Controlling for Realized Gains This table reports the estimation results for a modified version of regression model (4b). The dependent variable is the quarterly growth rate of book leverage (ΔBook Leverage). The key explanatory variables are the interaction terms between the quarterly growth rate of GDP (ΔGDP) and unrealized gains on AfS securities (Unrealized Gains AfS), realized gains on AfS and HtM securities (Realized Gains AfS & HtM), residual net income (Residual Net Income), the lagged total capital ratio (Total Capital Ratio$_{t-1}$), the quarterly growth rate of the average risk weight (ΔRisk Weight), and the lagged book leverage ratio (Book Leverage$_{t-1}$). For each interaction term we distinguish between ΔGDP>0 and ΔGDP<0 to account for potential non-linearities in effects across up- and downswings. Variables are defined in Table A1. For expositional purposes we multiply the accounting items with 1000 and ΔRisk Weight as well as Total Capital Ratio$_{t-1}$ with 100. Bank fundamentals are obtained from *SNL Financial* and real GDP is retrieved from the homepage of the *Bureau of Economic Analysis* (US Department of Commerce). This sample covers US commercial and savings banks during the time period Q1-1994 to Q1-2013. Clustered standard errors at the bank level are given in parentheses. Significance is indicated by: *** < 0.01, ** < 0.05, * < 0.10.

	Full Sample [1] ΔBook Leverage	**Savings Banks** [2] ΔBook Leverage	**CB < 20% FV** [3] ΔBook Leverage	**CB > 20% FV** [4] ΔBook Leverage
ΔGDP	1.482*	-1.897	2.644**	1.030
	(0.813)	(1.202)	(1.233)	(1.459)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP>0}$	0.042	0.138	0.220	-0.047
	(0.066)	(0.240)	(0.150)	(0.074)
ΔGDP * Unrealized Gains AfS * $1_{\Delta GDP<0}$	-0.198*	-0.177	-0.589***	0.114
	(0.107)	(0.261)	(0.206)	(0.120)
ΔGDP * Realized Gains AfS & HtM * $1_{\Delta GDP>0}$	0.993***	1.037	1.216**	0.929**
	(0.282)	(0.869)	(0.491)	(0.378)
ΔGDP * Realized Gains AfS & HtM * $1_{\Delta GDP<0}$	0.019	-0.308	0.107	-0.396
	(0.339)	(0.829)	(0.497)	(0.495)
ΔGDP * Residual Net Income * $1_{\Delta GDP>0}$	-0.014	0.152	-0.105	0.063
	(0.059)	(0.132)	(0.079)	(0.127)
ΔGDP * Residual Net Income * $1_{\Delta GDP<0}$	-0.191***	-0.137	-0.247***	-0.066
	(0.068)	(0.111)	(0.090)	(0.144)
ΔGDP * Total Capital Ratio$_{t-1}$ * $1_{\Delta GDP>0}$	-0.075***	0.004	-0.101**	-0.066
	(0.025)	(0.028)	(0.047)	(0.043)
ΔGDP * Total Capital Ratio$_{t-1}$ * $1_{\Delta GDP<0}$	-0.150***	0.003	-0.161**	-0.329***
	(0.033)	(0.036)	(0.068)	(0.074)
ΔGDP * ΔRisk Weight * $1_{\Delta GDP>0}$	0.006	-0.036	-0.023	0.075
	(0.034)	(0.087)	(0.053)	(0.052)
ΔGDP * ΔRisk Weight * $1_{\Delta GDP<0}$	-0.138**	0.000	-0.169*	-0.100
	(0.059)	(0.128)	(0.087)	(0.088)
ΔGDP * Book Leverage$_{t-1}$* $1_{\Delta GDP>0}$	-0.042	0.145	-0.083	-0.051
	(0.043)	(0.093)	(0.060)	(0.072)
ΔGDP * Book Leverage$_{t-1}$* $1_{\Delta GDP<0}$	0.225***	0.231*	0.171**	0.392***
	(0.060)	(0.118)	(0.080)	(0.116)
ΔTotal Assets	0.601***	0.764***	0.529***	0.667***
	(0.025)	(0.079)	(0.033)	(0.034)
Unrealized Gains AfS	-0.012***	-0.011***	-0.013***	-0.012***
	(0.001)	(0.002)	(0.001)	(0.001)
Realized Gains AfS & HtM	-0.021***	-0.023***	-0.022***	-0.021***
	(0.002)	(0.007)	(0.003)	(0.003)
Residual Net Income	-0.011***	-0.010***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Total Capital Ratio$_{t-1}$	0.001***	0.001	0.001**	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
ΔRisk Weight	-0.001***	0.001	-0.001**	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Bank Size$_{t-1}$	-0.008***	-0.009	-0.008***	-0.012***
	(0.002)	(0.008)	(0.002)	(0.003)
q_{t-1}	0.004***	-0.004	0.006***	0.004**
	(0.001)	(0.004)	(0.001)	(0.002)
Book Leverage$_{t-1}$	-0.004***	-0.006***	-0.005***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
$1_{\Delta GDP>0}$	-0.007***	-0.001	-0.008***	-0.004
	(0.002)	(0.004)	(0.002)	(0.003)
ΔGoodwill	-0.265***	-0.297***	-0.308***	-0.195***
	(0.023)	(0.102)	(0.031)	(0.029)
Constant	0.241***	0.311	0.231***	0.363***
	(0.040)	(0.198)	(0.048)	(0.076)
Observations	25889	3521	13405	8963
R^2	0.367	0.401	0.322	0.503
Bank Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	No	No	No	No
Clustering Level	Bank	Bank	Bank	Bank

Fishing with Pearls: The Value of Lending Relationships with Prestigious Firms *

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May 2018

Abstract

We provide novel evidence of banks establishing lending relationships with prestigious firms to signal their quality and attract future business. Using survey data on firm-level prestige, we show that lenders compete more intensely for prestigious borrowers and offer lower upfront fees to initiate lending relationships with prestigious firms. We also find that banks expand their lending after winning prestigious clients. Prestigious firms benefit from these relations as they face lower costs of borrowing even though prestige has no predictive power for credit risk. Our results are robust to matched sample analyses and a regression discontinuity design.

JEL Classification: G20; G21; G30; G32; L14; N20

Keywords: Lending Relationships; Firm Prestige; Bank Incentives

*Muermann, Rauter, and Scheuch are at WU (Vienna University of Economics and Business) and Vienna Graduate School of Finance (VGSF), Welthandelsplatz 1, Building D4, 1020 Vienna, Austria. We thank Tobias Berg, Hans Christensen, Alex Edmans, Rüdiger Fahlenbrach, Resi Guttmann, Ákos Horváth, Julian Kolm, Christian Laux, Christian Leuz, Gyöngyi Lóránth, Florian Nagler, Steven Ongena, Charlotte Østergaard, Roberto Pinto, Otto Randl, Michael Weber, Toni Whited, Josef Zechner as well as seminar participants at WU Vienna for helpful comments and suggestions. We are grateful to Alois Steinbichler and Jon Weiland for providing institutional information and many practical insights. Franziska Eberle and Stanka Mauerová provided excellent research assistance. This paper replaces an earlier draft titled "Prestige and Loan Pricing". Part of this research was completed while Rauter was visiting the University of Chicago Booth School of Business. Replication files are available at https://github.com/thomasrauter/fishing-with-pearls.

1 Introduction

A large literature examines the economic benefits of private information production by banks *within* lending relationships (e.g., Diamond, 1984; Rajan, 1992; Petersen and Rajan, 1994). However, lending relationships are also valuable to banks *outside* of specific firm-creditor ties. In practice, lenders frequently advertise their participation in syndicated loan transactions through "tombstone announcements" in financial magazines to raise their public profile (Carter and Manaster, 1990) and use existing lending relationships as a marketing tool to attract new borrowers.[1] Despite anecdotal evidence that banks value the public recognition from high profile transactions, we know little about how lending relationships with prestigious firms shape debt contracting.

In this paper, we examine the economic consequences of borrower prestige in the U.S. syndicated loan market. If firms have difficulties in assessing lenders' underwriting abilities, banks may use lending relationships with prestigious firms as credentials to signal their quality (e.g. Nelson, 1974; Bagwell and Ramey, 1994). Since lenders compete for high profile credentials, they may trade-off loan terms against the public recognition of their relationships and provide cheaper loans to prestigious firms. Our empirical tests provide strong support for this channel. We find that lenders compete more intensely for prestigious clients and offer lower upfront fees to initiate lending relationships with prestigious firms. After winning a prestigious borrower, banks expand their lending (to new firms) relative to otherwise similar institutions. Prestigious borrowers benefit from these relationships as they face lower costs of borrowing even though prestige has no predictive power for credit risk.

We use *Fortune's Most Admired Companies* survey to quantify borrower prestige. Since 1982, Fortune Magazine annually asks close to 15,000 analysts, outside directors, and executives to evaluate the public admiration of firms in the Fortune 1,000. To quantify

[1]Figure 1 shows US syndicated loan credentials that Royal Bank of Canada (RBC) used in client presentations in 2009. Figure 2 shows European syndicated loan credentials for UniCredit in 2013.

prestige, survey participants rate firms in their industry based on how much they admire them using a score between 0 (poor) and 10 (excellent). The questionnaire explicitly states that prestige ratings should be based on "respondents' firsthand knowledge of the companies or on anything they may have observed or heard about them." Using this particular survey to quantify prestige has the advantage that firms cannot actively influence their position in the final ranking since respondents are not directly affiliated with the firms they evaluate (Focke et al., 2017). Moreover, survey questions and variables are determined by a third party and do not change over time. We manually collect our prestige data from printed editions of the Fortune survey and use firms' overall score as our main measure of borrower prestige.

We begin our empirical analysis by investigating the impact of borrower prestige on firms' financing costs. We document that more prestigious firms face lower (total) costs of borrowing (Berg et al., 2016). The effect holds for different loan types and cost components and is robust to controlling for a large set of borrower characteristics, loan features, and (high-dimensional) fixed effects. The coefficient magnitude in our most conservative specification implies that a one standard deviation increase in prestige is associated with a reduction in total borrowing costs of 4.85% for the median loan.

Next, we show that borrower prestige is *not* associated with firms' credit ratings, credit default swap spreads, and implied recovery rates over the life of the loan. Thus, the cheaper financing for prestigious firms does not seem to be justified by a lower default probability, loss given default, or systematic risk. These results mitigate the concern that firm prestige does not causally impact borrowing costs but is rather associated with loan pricing because prestige is a proxy for credit risk capturing unobservable, time-varying firm characteristics.

We address the endogeneity of firm prestige more explicitly by exploiting discontinuous changes in prestige around rank 100 of the Fortune survey. The print media only focuses on the top 100 firms in the prestige ranking. For example, the New York Times and the Wall Street Journal do not print the entire ranking, but only include information on the top 100. The additional media coverage for firms within the top 100 leads to a positive, discontinuous jump in borrower prestige. Local changes in prestige are plausibly exogenous since random factors determine whether a firm is ranked just below or above 100 (e.g., mood of survey participants at the day of evaluation). We focus on firms with ranks 80 to 120 and make sure that loans on either side of the cutoff are virtually identical in terms of other borrower and loan characteristics. Consistent with our baseline results, we find a negative, significant jump in loan pricing but no break in credit risk for borrowers ranked below 100.

We validate the inferences from our regression discontinuity design by employing matched sample regressions as an alternative identification approach. Again, we consider firms as prestigious if they are included in the top 100 of the Fortune survey. Inclusion in the top 100 is likely based on criteria such as profitability or size and therefore not random. We alleviate this endogeneity concern by using (i) coarsened exact matching, (ii) nearest-neighbor matching, and (iii) propensity score matching to construct appropriate control samples based on a large set of pre-treatment financial characteristics. The results mirror those of our previous analyses.

Having established our main results, we next provide evidence that signaling by banks is a likely channel for the observed effects. First, we document that loan originations for prestigious firms experience fiercer bank competition. Holding everything else constant (including loan volume and firm size), borrower prestige is positively associated with both syndicate size and the portion of the loan that lead arrangers retain on their books. Moreover, the inverse effect of prestige on firms' financing costs is particularly strong for large syndicates, suggesting that banks' competition for prestigious clients drives down the cost of credit. Second, we document that prestigious firms pay lower upfront fees when they contract with a lead arranger for the first time. Thus, banks seem to make up-front fee concessions to *initiate* lending relationships with prestigious borrowers. Finally, banks that start lending to prestigious firms attract new borrowers and underwrite more syndicated loans *afterwards*.[2] We show that this result is not driven by an expansion strategy of the bank or concurrent but unrelated macroeconomic or regulatory changes.

Related Literature. We make two contributions relative to the existing literature. First, we contribute to the literature on firm-creditor relationships.[3] If there are informational frictions between investors and firms, banks generate private information by monitoring firms and thereby become inside creditors (Rajan, 1992; Berger and Udell, 1995; Stein, 2002; Berger et al., 2005). The informational advantage of banks creates value for firms by reducing agency conflicts and allowing for more efficient contracting (von Thadden, 1995; Rajan, 1992). Empirically, Bharath et al. (2011) find that repeated borrowing from the same lender yields lower spreads (in particular when borrower transparency is low), while banks are more likely offer further fee generating services to existing relationship borrowers (e.g., Drucker and Puri, 2005; Yasuda, 2005; Burch et al., 2005; Bharath et al., 2007). Fama (1985) and Diamond (1991) argue that bank relationships also generate value to borrowing firms outside the relationship since the renewal of bank loans serves as a positive signal to other lenders. By comparison, we document that financing a prestigious borrower creates value for the lender outside of the relationship since it serves as a credential which helps to compete for future clients.

Second, we contribute to a growing body of research that investigates the economic consequences of intangible assets. Edmans (2011) finds that companies with high levels of employee satisfaction generate superior long-run returns. Guiso et al. (2015) document that performance is stronger when employees view their top managers as trustworthy and

[2]In our bank-level analysis, we focus on lead arrangers since these institutions initiate, arrange, and manage the loan. It is the lead arranger that is primarily associated with the loan and most likely benefits from lending to a prestigious borrower.

[3]We refer to Ongena and Smith (1998) for a survey of this literature.

ethical. Both of these studies rely on surveys conducted among employees (insiders). In contrast, we study whether a company's perception by outsiders affects debt contracting. Hong and Liskovich (2015) find that socially responsible firms pay lower fines for bribing foreign government officials although corporate social responsibility is uncorrelated with bribe characteristics and judicial cooperation. The authors show that this bias is a halo effect and not prosecutorial conflict of interest. Our results are similar in spirit since the lower spreads and upfront fees that banks charge to prestigious borrowers are not justified by a lower credit risk over the life of the loan. We argue that bank-level incentives are the main driver of our results. Malmendier and Tate (2009) and Focke et al. (2017) examine the role of prestige in executive compensation. Malmendier and Tate (2009) show that prestigious CEOs with superstar status extract compensation benefits. Focke et al. (2017) document that the reverse also holds. They find that CEOs accept lower pay to work for prestigious firms because of status preferences and better subsequent career prospects. In contrast, we investigate the impact of firm prestige on loan contracting and show that prestige matters for the pricing of debt instruments over and above credit risk because lenders value relationships with prestigious firms.

2 Economic Mechanism and Empirical Predictions

Information asymmetry between lenders and borrowers is at the core of financial intermediation. Lenders invest in costly information production to assess the creditworthiness of potential borrowers, thereby reducing inefficiencies that arise from adverse selection. After loan contracting, lenders monitor borrowers to alleviate agency conflicts between managers and shareholders. Bank monitoring yields borrower-specific information that is durable, reusable (Boot and Thakor, 2000), and valuable if borrowers and lenders engage in repeated interactions.[4] Relationship borrowers may even be locked in due to the information asymmetries between outside lenders and the relationship lender (Sharpe, 1990; Rajan, 1992).

Lenders differ in their ability to underwrite and structure a loan for potential borrowers in a cost-efficient and timely manner. This heterogeneity in lenders' quality is particularly prevalent among lead arrangers in the syndicated loan market. Structuring a syndicated loan requires experience and a reliable network of other lenders that trust the lead arranger and are thus willing to timely commit to the syndicate. Potential borrowers might be less informed and therefore worry about the lender's quality. In this setting of asymmetric information, prestige can serve a signal about lenders' quality and thereby enhance the efficiency of lending (e.g. Nelson, 1974; Bagwell and Ramey, 1994).

Prestige is publicly observable, firm-specific information over which lenders compete to signal their quality to potential borrowers. The scarcity of lending relationships with prestigious borrowers equips them with bargaining power vis-à-vis lenders. Lenders in turn offer fee concessions to initiate high profile relationships. In the syndicated loan market, this translates into a higher number of participants in a deal and the lead arranger retaining a higher fraction of the loan.[5] For high-quality lenders, the benefit of signaling their quality to other clients is higher relative to low-quality lenders and they are willing to offer lower upfront fees to prestigious firms. The prestige of borrowers thus acts as a marketing tool that reveals lenders' quality and thereby reduces the inefficiency in lending due to asymmetric information.

This economic mechanism leads to the following empirical predictions. First, acquiring prestige as a valuable signal is costly and implies lower cost of borrowing for prestigious

[4]The association between past lending relationships and future bank business has been examined by Bharath et al. (2007) for the syndicated loan market, Drucker and Puri (2005) for seasoned equity offerings, and Yasuda (2005) and Burch et al. (2005) for public debt underwritings. They all find that existing lending relationships translate into a higher probability of repeated interaction.

[5]Ivashina (2009) shows that a higher lead bank's ownership of a loan also reduces asymmetric information between the lead and participants.

companies. Prestige is thus negatively related to the cost of borrowing. Second, prestige is unrelated to the creditworthiness of the borrower. Thus, prestige does not predict credit risk over the life of the underlying loan. Third, lenders compete for underwriting loans with prestigious borrowers. Prestige is thus positively related to the size of the syndicate and to the percentage retained by the lead arranger. Fourth, lenders use loans with prestigious borrowers as credentials and benefit by attracting more business with other clients. Underwriting loans with prestigious firms is therefore positively associated with the lead arranger's loan volume afterwards.

3 Data and Sample Selection

3.1 Measuring Borrower Prestige

We collect data on borrower-level prestige from Fortune's *Most Admired Companies* (MAC) survey. This survey is conducted once a year during fall among approximately 15,000 financial analysts, senior executives, and outside directors in the U.S. since 1982. Fortune magazine publishes the results in spring the following year and widely-read business newspapers such as the New York Times or the Wall Street Journal also provide coverage of the survey. To quantify firm-level prestige, Hay Group (on behalf of Fortune) asks survey participants to rate 10 companies in their industry among the Fortune 1000 based on how much they admire them in 8 different categories using a scale from 0 (poor) to 10 (excellent). The 8 categories are: (1) quality of management, (2) quality of products or services, (3) ability to attract, develop, and retain talented people, (4) wise use of corporate assets, (5) financial soundness, (6) innovativeness, (7) community and environmental responsibility, and (8) long-term investment. These attributes did not change since the inception of the survey in the 1980s. They were developed through interviews with executives and industry analysts to determine the qualities that make a company worthy of admiration. In the survey, only the attribute names are listed without any additional explanation or interpretation. Fortune asks survey participants to rate companies based on their firsthand knowledge or on anything they may have observed or heard about them. Therefore, the interpretation of the meaning of attributes is left to the respondents. The average of the 8 attribute scores determines the overall score of a company, which Fortune publishes every spring. In 2010, however, Fortune stopped reporting scores and only publishes industry ranks ever since.

Using Fortune's MAC ranking to define and quantify prestige has the advantage that firms cannot actively influence their inclusion or position in the survey (Focke et al., 2017). First, respondents are not directly affiliated to the companies they evaluate. Second, survey questions and variables are determined by a third party (Hay Group) and do not change over time. Third, it is arguably impossible for companies to find out the names of all survey respondents and to influence them accordingly. The number of firms included in the survey ranges from 183 to 535 per year with an average of 352.[6] We hand-collect the MAC surveys from printed editions of Fortune magazine between 1982 and 2009 and manually match them to our loan-level data.

3.2 Loan, Borrower and Bank Data

We obtain data on all dollar-denominated syndicated loans issued by U.S. firms from the Dealscan database maintained by the Loan Pricing Corporation (LPC).[7] We collect information on loan pricing, fees, size, maturity, seniority, type, collateral, covenants, and lenders. The unit of observation in the Dealscan database is a facility (or loan tranche). A syndicated loan package (or deal), however, typically consists of multiple potentially very

[6] Focke et al. (2017) point out that this variation is mainly driven by the number of industries included in the pool. Although the survey covers most industries, a significant fraction of companies comes from industries such as manufacturing, business equipment, and materials.

[7] We refer to Carey et al. (1998) and Chava and Roberts (2008) for a detailed description of the Dealscan database.

different facilities initiated at the same time. When we analyze the pricing implications of prestige on various fee and loan types, we use the loan-level information. We augment the Dealscan loan-level data by merging it with the comprehensive total cost of borrowing measure of Berg et al. (2016).[8]

For analyses that are based on variables determined at the deal level (syndicate size, lead share and measures for borrower-lender relationships), we follow the literature and choose the largest tranche to represent the deal. Carey et al. (1998) and Ivashina (2009) show that this selection procedure does not significantly affect the distribution of loans.

Using the Dealscan-Compustat Linking Database of Chava and Roberts (2008), we collect annual financial statement information for each borrower from Compustat. We use data from the fiscal year prior to the calendar year of loan origination to ensure that we only use accounting information that is publicly available at loan origination. For our bank level analysis, we also match annual financial statement information for lenders using the linking table provided by Schwert (2017) to our sample. We only focus on deals where we can identify a single lead arranger.[9] We define all variables we use in our empirical analysis and their respective data sources in Table A1.

3.3 Sample Selection and Descriptive Statistics

Our merged sample covers the time period 1982 to 2009. We exclude loans without an existing link to borrower information or missing borrower characteristics. We also exclude loans with non-positive facility amounts and maturities. We winsorize all continuous and unbounded variables at the 1% and 99% level to mitigate the effects of outliers. We are left with 45,837 loans to 7,328 U.S. borrowers between 1982 and 2009. Our key explanatory

[8]We are grateful for Tobias Berg providing the data on his homepage. We provide a detailed description of this measure in Section 4.

[9]Similar to Bharath et al. (2011) and Berg et al. (2016), we define a lender as a lead arranger if the lender is the sole lender or the lender role is reported as “Agent”, “Admin Agent”, “Arranger”, or “Lead bank”.

variable – the prestige score – is only defined for companies that are featured in Fortune's MAC survey. Therefore, our final sample consists of 4,285 loans to 540 borrowers. We draw on the larger initial sample, when we perform matching analyses between companies that are ranked among the top 100 MAC and those that are not featured in the survey.

Table 1 reports descriptive statistics for our sample. The average prestige score in our sample is 6.28 with a standard deviation of 0.99. About 3% of all loans in our sample are granted to borrowers which belong to the top 100 MAC. Figure 3 shows that the distribution of the prestige score is bell-shaped with a small negative skew. There is substantial variation in borrower prestige. Specifically, the range of the prestige score equals 6.76 with a minimum of 1.99 and a maximum of 8.75.

The average loan in our sample has a total cost of borrowing of about 140 basis points and a maturity of 47.72 months. The total cost of borrowing measures is available for about 48% of all loans in the sample. Approximately 24% of all loans have a reported upfront fee, 37% have a reported commitment fee, and 18% have a reported facility fee. The facility amount is skewed towards large loans with a mean of USD 321.21 million and a median of USD 100 million. 49% of all loans are secured and 42% feature financial covenants.

The average borrower in our sample has total assets of USD 11.67 billion. The distribution of assets is widely spread, in particular, the first and last decile of total assets are USD 0.05 billion and USD 16.91 billion, respectively. Thus, our sample covers both small and large borrowers. The average coverage is 34 with a median of 4.87 which is similar to Bharath et al. (2011). The average borrower has a leverage ratio of 34%, a profitability of -7%, tangibility of 35%, a current ratio of 61%, and a market-to-book ratio of 169%. About a third of all loans belong to borrowers with an investment grade rating, while 53% of all borrowers have no rating at all.

4 Borrower Prestige, Loan Pricing, and Credit Risk

We take a first look at the relation between borrower prestige and the cost of bank debt in Figure 4. The horizontal axis of the three scatter plots reports the prestige score and the vertical axes show the logarithm of the total cost of borrowing, the interest spread over LIBOR, and the upfront fee. The fitted lines indicate a strong negative unconditional relationship between borrower prestige and all three measures for the cost of borrowing.

We use three approaches to identify the effect of borrower prestige on outcome variables related to loan pricing. First, we apply fixed effects regressions with lagged firm controls to isolate the effect of borrower prestige on the cost of borrowing. Second, we exploit exogenous variation around rank top 100 of firms in the MAC rankings in a regression discontinuity analysis. Third, we use different matching estimators to evaluate the average treatment effect on a firm being ranked among the top 100 in the MAC ranking.

4.1 Fixed-Effects Regressions

To formally study the effect of borrower prestige on loan pricing, we estimate the following panel regression model

$$y_{l,i,t} = \alpha + \beta \cdot \text{Prestige}_{l,i,t-1} + \gamma \cdot X_{l,i,t(-1)} + \delta \cdot \text{Fixed Effects}_{l,i,j,t} + \varepsilon_{l,i,t}, \tag{1}$$

where subscripts l, i, j, and $t(-1)$ denote the loan, borrowing firm, industry, and (lagged) time period respectively. The dependent variable y is the logarithm of different measures for the cost of borrowing.[10]

Berg et al. (2016) show that the pricing structure of loan commitments is complex and includes a variety of fees. The most important fee types are the spread (interest margin above LIBOR paid on drawn portion of loan), the upfront fee (one-time fee paid at loan

[10] We use the logarithm to account for skewness in the data. Our results remain qualitatively unchanged if we use the level instead.

closing date), the commitment fee (one-time fee paid on unused loan commitments), and the facility fee (annual fee paid on total committed amount regardless of usage).[11] Importantly, different fees are used to price options embedded in loan contracts. For instance in credit lines, borrowers do not have to pay the committed spread until they actually choose to use the credit line. Furthermore, different fees can be used to screen borrowers' private information about the likelihood of future credit line usage. Lenders, therefore, typically use a combination of these fee types depending on borrower risk and loan type.

The total cost of borrowing (TCB) measure of Berg et al. (2016) reflects the option characteristics of bank loans and takes the likelihood of exercising these options as well as the different fees into account. The measure is defined as

$$\begin{aligned}
\text{TCB} = & \text{ Upfront Fee/Expected Loan Maturity in Years} \\
& + (1 - PDD) \cdot (\text{Facility Fee} + \text{Commitment Fee}) \\
& + PDD \cdot (\text{Facility Fee} + \text{Spread}) \\
& + PDD \cdot \text{Prob}(\text{Utilization} > \text{Utilization Threshold} \mid \text{Usage} > 0) \cdot \text{Utilization Fee} \\
& + \text{Prob}(\text{Cancellation}) \cdot \text{Cancellation Fee},
\end{aligned}$$

where PDD is the likelihood that a credit line is used, Prob(Utilization $>$ Utilization Threshold $|$Usage > 0) is the probability that the utilization of the credit line is higher than the threshold specified in the contract conditional on observing usage, and Prob(Cancellation) is the probability that the loan will be canceled. We use TCB as the main measure of loan pricing throughout the most part of our analysis.

Our measure of prestige is the borrower's overall score in Fortune's MAC survey. Our main coefficient of interest is β, which captures the relation between borrower prestige and

[11] Unfortunately, we do not have enough observations to test the effect of borrower prestige on other less common fee types such as utilization and cancellation fees.

the cost of borrowing. We lag the prestige score by one year to ensure that our measure captures survey results prior to loan origination. This timing convention implies that the variable does not reflect elements that result from the issuance of the loan (reverse causality). For example, it might be the case that survey participants (e.g., financial analysts) take into account recent news on loan contracting when evaluating the prestige of a particular borrower.

X denotes the vector of control variables. It includes loan and borrower characteristics that directly affect the cost of bank loans or simultaneously drive borrower prestige and loan pricing. On the loan level, we follow the literature and control for loan size, maturity, number of facilities, whether the loan is secured, has financial covenants, prime as base rate, or performance pricing. On the borrower level, we control for firm size, the coverage ratio, leverage, profitability, tangibility, the current ratio, and the market-to-book ratio. All borrower characteristics are lagged by one year to avoid an overlap with the period of loan issuance. Throughout most of our analysis and following the literature on loan pricing, Fixed Effects is a vector of loan type, loan purpose, rating, industry, as well as year dummies. ϵ denotes the vector of regression disturbances.

We estimate the above regression model with multi-level fixed effects by applying the feasible and computationally efficient estimator of Correia (2016). Importantly, the estimator eliminates singleton observations which typically arise in model with multi-level fixed effects and which might overstate statistical significance. As loans to the same borrower might be correlated with each other, we adjust standard errors for within firm-clusters (e.g., Petersen, 2009; Valta, 2012; Hertzel and Officer, 2012).

Table 2 reports the coefficient estimates of model (1) for TCB with the prestige score as the key explanatory variable. In the first column, we report our main regression specification – controlling for loan features and borrower characteristics, including rating, industry, year, loan type and purpose fixed effects, and standard errors clustered at the firm level. We find that the coefficient of the lagged prestige score is negative and highly statistically significant (coefficient: -0.049, t-statistic: -3.11). To alleviate concerns, that the time fixed-effect does not appropriately account for industry dynamics, we include industry-year fixed effects. The results remain virtually the same (coefficient -0.048, t-statistic: 3.24). Similarly, results do not change either when we include loan-purpose-year and loan-type-year fixed effects (coefficient: -0.042, t-statistic: 2.70) to account for purpose and type specific invariant unobservables. We also replace rating fixed effects by firm fixed effects in our baseline specification to control for firm-specific time-invariant observables which yields a lower point estimate (coefficient: -0.072, t-statistic: 3.77). We also employ state-level clustering for some specifications which, however, does not impair the significance of our estimates.

Overall, the coefficient estimate is similar across most of the specifications. In our main regression specification, the coefficient of the prestige score equals -0.049 and is significant at the 1% level. Importantly, the negative relation between borrower prestige and the cost of borrowing is also economically significant. An increase in borrower prestige by one standard deviation (0.99) reduces the TCB by 4.85% on average. For the median loan in our sample, this translates into an annual reduction of the TCB by about 5 basis points.

The estimates of the control variables have the expected sign. The coefficient of the loan amount is negative and statistically significant which suggests that firms with larger financing needs receive cheaper funding due to positive economies of scale. In contrast, the number of facilities is positively related to the TCB. One likely explanation might be that loans with a higher number of tranches are more difficult to structure and arrange for banks. Consequently, the lender demands higher spreads from the borrower as compensation. Surprisingly, secured loans have significantly higher borrowing costs. As discussed by Hertzel and Officer (2012), this is a common finding in nearly all empirical studies using Dealscan data. It is the result of this variable capturing variation in credit risk that is not picked up by the other control variables. The coefficient of the prime base rate dummy is negative and weakly statistically significant which suggests that loans which are based on the U.S. prime rate have lower borrowing costs compared to loans which are tied to LIBOR. In line with the existing literature, the TCB is higher for loans with shorter maturities, loans with financial covenants and loans which feature a performance pricing schedule. Moreover, the costs of borrowing are significantly higher for borrowers with high leverage, consistent with structural models of credit risk (e.g. Black and Scholes, 1973; Merton, 1974). Borrowers with higher interest coverage and market-to-book ratios (i.e. higher growth opportunities), on the other hand, face lower borrowing costs.

Next, we investigate the impact of borrower prestige on alternative measures for the cost of borrowing and individual fee types in Table 3. In Panel A, we find that the coefficients of prestige are negative and highly statistically significant for the spread (interest spread over LIBOR), AISD (spread plus facility fee), AISU (commitment fee and facility fee). On the fee level, we find a statistically significant negative impact of borrower prestige on upfront fees and the facility fee in Panel B. We do not find strong evidence that prestigious borrowers pay lower commitment fees (i.e. fees on unused loan commitments).

As discussed above, loan contracts differ substantially with respect to embedded option characteristics. In particular, the spread of term loans and credit lines are fundamentally different objects – in term loan contracts, borrowers have to pay the spread on a regular basis, while in credit line contracts, borrowers pay the spread only when they decide to exercise the option to draw on the credit line. We test whether there are significant differences between the effect of prestige on term loans and credit lines. Therefore, we restrict our sample to loans that we can identify as either of the two loan types. The results are reported in Table 4. We find evidence for lower TCB, loan spreads, and upfront fees for credit lines of prestigious borrowers compared to term loans. We do not find that facility fees are significantly different between the two loan types. We also perform F-tests to test whether the effect of prestige is also negative and significant for credit lines overall. Indeed, we find that prestige negatively affects all four measures of borrowing costs for credit lines.

We have established that prestigious borrowers face lower costs of borrowing. However, borrower prestige might just capture unobservable firm characteristics that banks take into account when negotiating loan contracts. Our measure of borrower prestige would thus pick up unobserved heterogeneity across firms and time which we cannot control for in our baseline panel regression model. If this channel is driving our result, we expect borrower prestige to have predictive power for companies' credit risk. The credit risk channel has at least three components which should matter for loan contracting – the probability of default, the recovery in default, and a firm's systematic risk.

We use three measures for credit risk to account for these three dimensions – the average S&P long-term rating from loan issuance to maturity ($\overline{Rating}$), the average Markit implied recovery from loan issuance to maturity ($\overline{Recovery}$), and the average five year Markit CDS spread from loan issuance to maturity ($\overline{CDS\ Spread}$).[12] We take averages over a loan's life to account for the different paths these variables might have over time.[13] The model specification is essentially the same as in (1). We also add the loan spread as an additional control variable to take into account the mechanical effect of interest rate payments on credit risk. Without controlling for the loan spread, the coefficients of our prestige variables are downward biased since borrower prestige and spreads are negatively related, while spreads and credit risk are positively related. However, this bias does not

[12] While S&P ratings are available for the whole sample period, Markit CDS spreads and implied recoveries are only available from 2001 on.

[13] As a robustness, we conduct the same analysis using values at maturity and changes from issuance to maturity. The results are the same and are available in the Internet Appendix Table IA1.

affect our inference since it only makes it more difficult *not* to find an effect of borrower prestige on default risk.

Table 5 presents the results of our credit risk analysis. The coefficients of our prestige measure are insignificant for all three measures of credit risk and irrespective of whether we include the spread as a control. The lower costs of borrowing thus do not seem to be justified by lower credit risk over the life of a loan.

The results of our credit risk analysis imply that the effect of borrower prestige on loan pricing is not driven by asymmetric information either. If prestige served as a signal of borrower quality at loan issuance, we should find an inverse relation between prestige and default *ex-post* due to adverse selection. Overall, banks seem to provide prestigious firms with better pricing terms for reasons that are unrelated to default-relevant fundamentals.

4.2 Regression Discontinuity Design

To support the results of the fixed effects regressions, we perform a regression discontinuity analysis around rank 100 to exploit locally exogenous changes around this threshold.[14] Fortune magazine publishes its MAC ranking every spring and widely-read business newspapers then provide coverage on the survey. In this context, the print media focuses on the top 100 firms in the ranking. For example, the New York Times and the Wall Street Journal do not print the entire ranking but only include information on the top 100. Moreover, companies themselves frequently issue press releases if they are ranked among the top 100 most admired companies. We argue that the *additional* media and press coverage for companies within the top 100 leads to a discontinuous, positive jump in borrower prestige. Importantly, local changes in borrower prestige are exogenous around rank 100 since random factors (e.g., mood of survey participants at the time of evaluation)

[14] We adopt this approach from Focke et al. (2017), who perform a regression discontinuity analysis around rank 100 using Fortune's list of the *Best Companies to Work for* and Fortune's *Most Admired Companies* ranking.

determine whether a company is ranked just below or just above 100.

In our regression discontinuity analysis, we focus on firms ranked between 80 and 120. These companies are differentially affected by the treatment but very similar with respect to other firm characteristics (e.g., profitability, size, etc.). If borrower prestige has a causal effect on loan pricing, we should find a discontinuous jump in the TCB around rank 100. We have to ensure that the estimates of the treatment effect are not biased by heterogeneity in other firm characteristics. Therefore, we perform our analysis not only for the raw outcome variables but also for their residuals, which we obtain from linear regressions that control for these fundamentals. We only consider loans that are originated between April and December because Fortune magazine publishes its MAC survey between January and March each year.

Figure 5 provides graphical evidence for our regression discontinuity analysis. Consistent with our previous analysis, we see a discontinuous, negative jump in the total cost of borrowing for loans ranked below 100. In contrast, we do not find any statistically and economically significant jump in credit risk around rank 100.[15] In Table 6 we report the corresponding point estimates. We find a negative statistically significant coefficient for the total cost of borrowing both without controlling for any firm or loan characteristics and with including covariates. The results are still significant when we apply the bias-corrected robust variance estimator of Calonico et al. (2017). For credit risk, we find a significant negative coefficient without controlling for firm and loan characteristics, however, the effect vanishes once we include covariates. To corroborate our findings, we perform placebo tests around rank 150. Borrower prestige should not change exogenously since there is no media effect at this threshold. Indeed, we find that there is either a positive effect for the total cost of borrowing, or no effect at all for all other models.

[15] We use the average borrower rating over a loan's life as our measure of credit risk. Unfortunately, we do not have enough observations to perform the analysis on our other measures of credit risk, i.e. CDS spreads and implied recovery.

Taken together, the results support out notion that borrower prestige reduces the cost of borrowing, but does not predict credit risk. Next, we use the top 100 cutoff to construct a further measure of prestige – a dummy variable which indicates whether a company is in the top 100 of the MAC ratings.

4.3 Matched Sample Analyses

Because being in the top 100 was not randomaly assigned, the pretreatment covariates differ between treated and control groups. To account for this endogeneity problem, we apply several matching estimators.

The first class of matching estimators we use is coarsened exact matching (CEM) (Iacus et al., 2012). CEM is a matching method where the balance between treated and control group is chosen ex ante through coarsening. The CEM algorithm coarsens variables into groups and assigns them the same numerical value. Then, exact matching is applied to the coarsened data to determine matches and prune unmatched observations. Only uncoarsened values of the matched data are then used in regressions. The CEM procedure thereby automatically restricts the matched data to areas of common empirical support.

As a fist step, we calculate the imbalance between treated and untreated observations by computing the $\mathcal{L}_1$ distance which is a measure of imbalance bounded between 0 (perfect balance) and 1 (complete separation). Table 7 shows the imbalance and the differences in mean and median between treated and control groups before and after CEM. The imbalance is largest with respect to total assets, coverage, leverage and market-to-book ratio. We first apply the CEM algorithm on total assets and leverage and use the resulting matches in our baseline regressions specification. Table 8 shows the regression results on the coarsened-exact matched samples. We find a significant negative effect of the top 100 dummy on the total cost of borrowing (coefficient: -0.081, t-statistic: -3.26). We then apply the CEM algorithm on total assets, coverage, leverage, and market-to-book ratio to further reduce the imbalance. The estimate remains essentially unchanged (coefficient: -0.085, t-statistic: -3.39).[16] Also consistent with our previous results, we do not find any effect of the top 100 dummy on credit risk as measured by the average rating for both matched samples.

The second class of matching estimators belongs to approximate matching methods which specify some metric to find a control group that is close to the treated observations. We apply two commonly used approximate matching methods as robustness checks – nearest-neighbor matching (NNM) and propensity score matching (PSM). In both cases, we are interested in the average treatment effect on the treated (ATET) of firms ranked in the top 100 of the MAC.

NNM uses some distance metric between covariate patterns of treated firms to find the closest matches among control firms. Since using more than one continuous covariate in NNM introduces a large sample bias, we employ the bias-adjustment proposed by Abadie and Imbens (2006, 2011). Panel A of Table 9 shows the ATET for different NNM specifications. We match on borrower characteristics in all models and find a negative significant coefficient on the top 100 dummy for 1 or 10 neighbors. Since there might also be an endogeneity problem with respect to the loans prestigious companies actually issue, we also match on loan features in addition to firm characteristics. The results are statistically significant and consistent with our previous analyses across all models. When we also match on loan features, the magnitudes are similar to previous point estimates.

PSM matches on the estimated probability of being treated (propensity score). Estimating the ATET only requires finding matches for the treated observations. Since the typical derivative-based standard error estimators cannot be used in this case, we rely on the non-parametric method derived in Abadie and Imbens (2016) to compute standard

[16] Matching on all borrower characteristics unfortunately does not yield enough observations for meaningful statistical inference.

errors. Again, we apply different models – matching on firm characteristics only, matching on loan features and firm characteristics, using different number of neighbors – and find a statistically significant negative coefficient on the top 100 dummy in Panel B of Table 9. However, the results for the PSM are quantitatively lower by a magnitude of two compared to our previous analyses and should therefore interpreted with caution.

5 Why Does Prestige Affect Loan Pricing?

5.1 Borrower Prestige and Bank Competition

After having established that prestigious borrowers get better terms in their loan contracting, we investigate which channel drives these results. Our third hypothesis states that lenders compete for prestigious borrowers. Since the additional key variables are determined at the deal level, we focus on the largest facility of each package to represent the deal in the following analyses.

Competition for prestigious borrowers creates a tension between the number of lenders able to participate in a deal and the allocation the lead bank retains. Prestigious borrowers attract more (potential) lenders who value the participation in a deal with these companies and therefore compete for being part of the syndicate. Prestige should therefore positively predict the syndicate size (i.e. the number of participating lenders). The lead bank, however, might have an incentive to retain a larger allocation of a deal with a prestigious company for various reasons, e.g. build up a lending relationship or strengthen the signal that it is a high quality lender. Indeed, we find that prestige positively predicts the syndicate size and the lead share in Table 10.

Table 10 also provides evidence that lenders are willing to accept concessions for being part of a deal as measured by including the interaction of prestige and syndicate size in our main regression specification – deals with a larger syndicate have higher total cost of borrowing, but prestigious companies seem to get a rebate when they contract with a larger syndicate. We do not find significant evidence for a similar effect for higher lead shares.

5.2 The Role of Lending Relationships

If lending to prestigious borrowers is valuable to lenders, then lenders might offer extra favorable pricing terms in order to attract prestigious borrowers. We thus define the variable *New Relation* as a dummy variable equal to one if the lead bank lends to the borrower for the first time, and zero otherwise.[17] It quantifies whether the effect of borrower prestige on loan pricing is stronger for new bank relationships.

In Table 11, we find that the coefficient of the interaction term is negative and statistically significant for upfront fees but insignificant for the total cost of borrowing. Therefore, banks seem to make upfront fee concessions to start new lending relationships with prestigious firms. This results is consistent with the competition channel we highlight above – lenders use lower upfront fees to compete for lending relationships with prestigious borrowers. The insignificant interaction term for the total cost of borrowing implies that lenders only use a rebate in upfront fees rather than a reduction in the overall cost.

We also examine how lending relationships with prestigious companies evolve over time. We construct the relationship lending variables in the spirit of Bharath et al. (2011) who find that repeated borrowing from the same lender translates into lower spreads. The measures of relationship lending include a dummy variable equal to one if a borrower and a lender interacted in the last five years before a deal (*Old Relation (Dummy)*), the share of the number of loans between a borrower and a lender as a fraction of the total number

[17]Since our sample starts in 1982, we cannot observe the entire lending history of our borrowers. We do not define the relationship dummy variables for the first loan of every borrower to make sure that they are not artificially equal to one. Our results are qualitatively unchanged if we start defining these variable at each borrower's third or fourth loan instead.

of loans of a borrower in the last five years before a deal (*Old Relation (Number)*), and the share of the loan amount between a borrower and a lender as a fraction of the total loan amount of a borrower in the last five years before a deal (*Old Relation (Amount)*). We find that existing relationships reduce the average upfront fees paid by lenders, prestigious companies, however, pay higher upfront fees in repeated interactions. We do not find any statistically significant evidence for the effect of lending relationships on the total cost of borrowing.

Taken together, these results indicate that lenders are willing to make price concessions to establish a relationship with a prestigious borrower. These borrowers then pay relatively higher upfront fees in the following deals. This is consistent with our hypothesis that lending to prestigious companies yields attractive future lending opportunities.

5.3 Future Bank Business

As we have established above, incentives at the bank level might provide an explanation of the effect of borrower prestige on loan pricing. It is common practice that banks use loans with prestigious borrowers as a marketing tool in client presentations to attract future business (see Figures 1 and 2). The reduction in borrowing costs resembles the value that banks attach to the value of relationships with prestigious companies.

In this analysis, we collapse the deal-level data to bank-year level variables and examine whether lending to prestigious companies in a given year leads to higher bank business in subsequent years. We consider four different measures of annual bank business – the total annual loan volume underwritten, the average volume per loan, the total number of loans per year, and the number of unique borrowers a lead bank contracted with. The key explanatory variable *Top 100 Loans* is defined as the number of loans that a lead bank has underwritten for borrowers ranked among the top 100 most admired companies. We control for banks' total assets, market-to-book ratios, and deposits over assets ratios.[18] See Table 12 for descriptive statistics of the bank-level sample. We include bank fixed-effects to control for unobserved heterogeneity that is constant within banks and year fixed-effects to control for macroeconomic conditions.

We report the results of our bank-level analysis in Panel A of Table 13. Consistent with our hypothesis, we find that the effect of the number of top 100 loans on the total loan volume in subsequent years is positive and statistically significant. We further show that this increase in deal volume is not driven by an increase in the average volume per loan, but rather by an increase in the number of loans that the lead bank underwrites. The insignificant estimate for the volume per loan is in line with borrowers having financing needs that are unrelated to the intensity with which banks lend to prestigious companies. Interestingly, not only the number of loans but also the number of unique borrowers – a measure of the broadness of a bank's customer base – increases after banks lend to prestigious firms. In Panel B of Table 13, we show that these findings hold up to a two year lag. One explanation for the lack of persistence in the effect might be that banks mainly use credentials with prestigious firms from recent deals to attract new business.

Overall, our findings support the idea that prestigious firms receive cheaper funding because the associated lending relationship helps banks to establish valuable credentials they use to successfully compete for future business.

6 Conclusion

Despite anecdotal evidence that banks value the public recognition from high profile transactions, we know little about how lending relationships with prestigious firms shape debt contracting. In this paper, we provide novel evidence of banks establishing lending relationships with prestigious firms to signal their quality and attract future business.

[18] The results remain qualitatively unchanged if we include tier 1 ratios as a measure of banks' financial constraints. The results can be found in Internet Appendix Tables IA2 and IA3.

Using survey data on firm-level prestige, we show that lenders compete more intensely for prestigious clients and offer lower upfront fees to initiate lending relationships with prestigious firms. We also find that banks expand their lending after winning prestigious borrowers. Prestigious firms benefit from these relationships as they face lower costs of borrowing even though prestige has no predictive power for credit risk.

Our results should be interpreted with the following caveats in mind. First, although the negative association between firm prestige and financing costs is statistically significant across our different econometric approaches, its economic magnitude varies and readers should therefore interpret the corresponding coefficients with care. Second, firm prestige might have sizeable volume effects on other financial services. For instance, banks may use credentials from the syndicated loan market to cross-sell equity underwritings or M&A advisory and vice-versa (e.g., Laux and Walz, 2009). Finally, firm prestige might also matter in other service industries such as auditing. We leave the investigation of these other settings to future research.

References

Abadie, A. and G. W. Imbens (2006). Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica 74*(1), 235–267.

Abadie, A. and G. W. Imbens (2011). Bias-Corrected Matching Estimators for Average Treatment Effects. *Journal of Business & Economic Statistics 29*(1), 1–11.

Abadie, A. and G. W. Imbens (2016). Matching on the Estimated Propensity Score. *Econometrica 84*(2), 781–807.

Bagwell, K. and G. Ramey (1994). Advertising and Coordination. *Review of Economic Studies 61*(1), 153–171.

Berg, T., A. Saunders, and S. Steffen (2016). The Total Cost of Corporate Borrowing in the Loan Market: Don't Ignore the Fees. *Journal of Finance 71*(3), 1357–1392.

Berger, A. N., N. N. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein (2005). Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks. *Journal of Financial Economics 76*(2), 237–269.

Berger, A. N. and G. F. Udell (1995). Relationship Lending and Lines of Credit in Small Firm Finance. *Journal of Business 68*(3), 351–382.

Bharath, S., S. Dahiya, A. Saunders, and A. Srinivasan (2007). So What Do I Get? The Bank's View of Lending Relationships. *Journal of Financial Economics 85*(2), 368 – 419.

Bharath, S. T., S. Dahiya, A. Saunders, and A. Srinivasan (2011). Lending Relationships and Loan Contract Terms. *Review of Financial Studies 24*(4), 1141–1203.

Black, F. and M. Scholes (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy 81*(3), 637–654.

Boot, A. W. A. and A. V. Thakor (2000). Can Relationship Banking Survive Competition? *Journal of Finance 55*(2), 679–713.

Burch, T. R., V. Nanda, and V. Warther (2005). Does it Pay to be Loyal? An Empirical Analysis of Underwriting Relationships and Fees. *Journal of Financial Economics 77*(3), 673–699.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik (2017). Regression Discontinuity Designs Using Covariates. Working paper.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2015). Optimal Data-Driven Regression Discontinuity Plots. *Journal of the American Statistical Association 110*(512), 1753–1769.

Carey, M., M. Post, and S. A. Sharpe (1998). Does Corporate Lending by Banks and Finance Companies Differ? Evidence on Specialization in Private Debt Contracting. *Journal of Finance 53*(3), 845–878.

Carter, R. and S. Manaster (1990). Initial Public Offerings and Underwriter Reputation. *Journal of Finance 45*(4), 1045–1067.

Chava, S. and M. R. Roberts (2008). How Does Financing Impact Investment? The Role of Debt Covenants. *Journal of Finance 63*(5), 2085–2121.

Correia, S. (2016). A Feasible Estimator for Linear Models with Multi-Way Fixed Effects. Working paper.

Diamond, D. W. (1984). Financial Intermediation and Delegated Monitoring. *Review of Economic Studies 51*(3), 393–414.

Diamond, D. W. (1991). Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt. *Journal of Political Economy 99*(4), 689–721.

Drucker, S. and M. Puri (2005). On the Benefits of Concurrent Lending and Underwriting. *Journal of Finance 60*(6), 2763–2799.

Edmans, A. (2011). Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices. *Journal of Financial Economics 101*(3), 621–640.

Fama, E. F. (1985). What's Different About Banks? *Journal of Monetary Economics 15*(1), 29–39.

Focke, F., E. Maug, and A. Niessen-Ruenzi (2017). The Impact of Firm Prestige on Executive Compensation. *Journal of Financial Economics 123*(2), 313 – 336.

Guiso, L., P. Sapienza, and L. Zingales (2015). The Value of Corporate Culture. *Journal of Financial Economics 117*(1), 60 – 76.

Hertzel, M. G. and M. S. Officer (2012). Industry Contagion in Loan Spreads. *Journal of Financial Economics 103*(3), 493–506.

Hong, H. and I. Liskovich (2015). Crime, Punishment and the Halo Effect of Corporate Social Responsibility. NBER Working paper.

Iacus, S. M., G. King, and G. Porro (2012). Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis 20*(1), 1–24.

Ivashina, V. (2009). Asymmetric Information Effects on Loan Spreads. *Journal of Financial Economics 92*(2), 300–319.

Laux, C. and U. Walz (2009). Cross-Selling Lending and Underwriting: Scope Economies and Incentives. *Review of Finance 13*(2), 341–367.

Malmendier, U. and G. Tate (2009). Superstar CEOs. *Quarterly Journal of Economics 124*(4), 1593–1638.

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance 29*(2), 449–470.

Nelson, P. (1974). Advertising as Information. *Journal of Political Economy 82*(4), 729–754.

Ongena, S. and D. C. Smith (1998). Bank Relationships: A Review. In H. P. and Z. S. A. (Eds.), *The Performance of Financial Institutions*. Cambridge, UK: Cambridge University Press.

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies 22*(1), 435–480.

Petersen, M. A. and R. G. Rajan (1994). The Benefits of Lending Relationships: Evidence from Small Business Data. *Journal of Finance 49*(1), 3–37.

Rajan, R. G. (1992). Insiders and Outsiders: The Choice Between Informed and Arm's-Length-Debt. *Journal of Finance 47*(4), 1367–1400.

Schwert, M. (2017). Bank Capital and Lending Relationships. *Journal of Finance, Forthcoming*.

Sharpe, S. A. (1990). Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships. *Journal of Finance 45*(4), 1069–1087.

Stein, J. C. (2002). Information Production and Capital Allocation: Decentralized versus Hierarchical Firms. *Journal of Finance 57*(5), 1891–1921.

Valta, P. (2012). Competition and the Cost of Debt. *Journal of Financial Economics 105*(3), 661–682.

von Thadden, E.-L. (1995). Long-Term Contracts, Short-Term Investment and Monitoring. *Review of Economic Studies 62*(4), 557–575.

Yasuda, A. (2005). Do Bank Relationships Affect the Firm's Underwriter Choice in the Corporate-Bond Underwriting Market? *Journal of Finance 60*(3), 1259–1292.

Tables

Table 1: Descriptive Statistics for Facility-Level Sample

This table reports descriptive statistics for key variables of the empirical analysis. For each variable, the number of observations (N), mean, standard deviation (SD), 10% quantile ($Q_{0.10}$), 25% quantile ($Q_{0.25}$), median ($Q_{0.50}$), 75% quantile ($Q_{0.75}$), and 99% quantile ($Q_{0.99}$) are reported. Prestige variables are obtained from *Fortune's Most Admired Companies* surveys. Loan and borrower characteristics are collected from *Dealscan* and *Compustat*, respectively. The overall sample covers 45,837 loans to 7,328 US borrowers between 1982 and 2009. We define all variables in Table A1.

	N	Mean	SD	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
Prestige Variables								
Prestige [0-10]	4,285	6.28	0.99	5.05	5.66	6.34	6.97	7.50
Top 100 [0/1]	45,837	0.04	0.19	0.00	0.00	0.00	0.00	0.00
Loan Characteristics								
TCB [bps]	22,207	139.56	124.19	26.94	49.15	102.94	187.05	308.95
AISD [bps]	37,957	200.09	148.43	37.50	75.00	175.00	275.00	380.00
AISU [bps]	22,237	31.44	23.93	8.00	13.00	25.00	50.00	50.00
Spread [bps]	31,522	170.00	130.95	27.50	62.50	150.00	250.00	325.00
Upfront Fee [bps]	11,350	63.22	82.70	9.00	16.66	38.05	87.50	150.00
Commitment Fee [bps]	16,767	36.88	54.74	12.50	25.00	37.50	50.00	50.00
Facility Fee [bps]	8,115	19.27	24.25	6.00	8.00	12.50	22.22	37.50
Amount [USD mn.]	45,837	321.21	864.30	6.00	24.96	100.00	300.00	750.00
Maturity [months]	45,837	47.72	33.46	12.00	23.00	47.00	60.00	84.00
Facilities [number]	45,837	1.90	1.25	1.00	1.00	2.00	2.00	3.00
Secured [0/1]	45,837	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Financial Covenants [0/1]	45,837	0.42	0.49	0.00	0.00	0.00	1.00	1.00
Prime Base Rate [0/1]	45,837	0.58	0.49	0.00	0.00	1.00	1.00	1.00
Performance Pricing [0/1]	45,837	0.31	0.46	0.00	0.00	0.00	1.00	1.00
Credit Line [0/1]	45,837	0.60	0.49	0.00	0.00	1.00	1.00	1.00
Term Loan [0/1]	45,837	0.27	0.44	0.00	0.00	0.00	1.00	1.00
Number of Lenders	45,720	7.09	8.75	1.00	1.00	4.00	9.00	18.00
Lead Share [0-1]	14,572	0.58	0.39	0.10	0.19	0.50	1.00	1.00
New Relation [0/1]	36,439	0.64	0.48	0.00	0.00	1.00	1.00	1.00
Old Relation (Dummy) [0/1]	36,439	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Old Relation (Number) [0-1]	26,070	0.34	0.41	0.00	0.00	0.00	0.67	1.00
Old Relation (Amount) [0-1]	26,069	0.36	0.43	0.00	0.00	0.00	0.88	1.00
Average Rating [1-15]	18,909	10.16	3.55	5.86	7.67	10.00	13.00	14.46
Average Recovery [number]	4,036	0.39	0.04	0.37	0.40	0.40	0.40	0.40
Average CDS Spread [number]	3,971	0.02	0.04	0.00	0.01	0.01	0.02	0.04
Borrower Characteristics								
Total Assets [USD bn.]	45,837	11.67	70.32	0.05	0.16	0.72	3.56	16.91
Coverage [number]	45,837	34.06	813.58	0.81	2.38	4.87	10.56	24.93
Leverage [number]	45,837	0.34	0.26	0.07	0.18	0.32	0.46	0.62
Profitability [number]	45,837	-0.07	9.36	0.02	0.07	0.13	0.22	0.36
Tangibility [number]	45,837	0.35	0.24	0.06	0.14	0.29	0.52	0.73
Current Ratio [number]	45,837	0.61	6.17	0.07	0.16	0.31	0.52	0.89
Market-to-Book [number]	45,837	1.69	1.73	0.95	1.09	1.36	1.84	2.66
Investment Grade [0/1]	21,655	0.33	0.47	0.00	0.00	0.00	1.00	1.00
Not Rated [0/1]	45,837	0.53	0.50	0.00	0.00	1.00	1.00	1.00

Table 2: Impact of Borrower Prestige on Total Cost of Borrowing

This table provides results for linear regressions of the total cost of borrowing (TCB) on the prestige score, loan features, and borrower characteristics. The dependent variable is the logarithm of the TCB. The key explanatory variable is the lagged prestige score from Fortune's Most Admired Companies surveys, which can take any value between 0 and 10. Column (1) shows results for our main regression model with rating, industry (one-digit IC code), year, loan type and loan purpose fixed effects. In column (2), we replace industry and year fixed effects by industry-year fixed effects. In column (3), we replace loan type and purpose fixed effects by loan-type-year and loan-purpose-year fixed effects. Column (4) shows the results for firm fixed effects instead of rating fixed effects. In column (5), we use industry-year, loan-type-year, loan-purpose-year, and firm fixed effects. Standard errors are clustered at the borrower level in columns (1)-(5). Columns (6)-(8) show the results for state-level clustering of the specifications used in columns (1), (2) and (5). The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm or state level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(TCB)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prestige_{t-1}	-0.049***	-0.048***	-0.042***	-0.072***	-0.093***	-0.046**	-0.048***	-0.105***
	(-3.11)	(-3.24)	(-2.70)	(-3.77)	(-5.38)	(-2.52)	(-2.85)	(-6.18)
Log(Amount)_t	-0.066***	-0.071***	-0.061***	-0.071***	-0.043***	-0.065***	-0.070***	-0.044***
	(-4.39)	(-4.97)	(-4.47)	(-4.27)	(-2.98)	(-4.74)	(-5.82)	(-3.44)
Log(Maturity)_t	-0.274***	-0.266***	-0.263***	-0.276***	-0.257***	-0.253***	-0.253***	-0.241***
	(-8.05)	(-8.54)	(-7.00)	(-8.24)	(-7.24)	(-9.03)	(-8.92)	(-5.72)
Facility Number_t	0.054***	0.055***	0.056***	0.057***	0.048**	0.057***	0.059***	0.058*
	(3.78)	(3.85)	(3.77)	(3.09)	(2.44)	(4.04)	(4.12)	(1.89)
Secured_t	0.539***	0.550***	0.591***	0.553***	0.555***	0.519***	0.530***	0.567***
	(13.28)	(14.07)	(12.25)	(12.10)	(11.25)	(14.32)	(14.93)	(10.66)
$\text{Financial Covenants}_t$	0.065**	0.047	0.040	0.000	-0.012	0.054*	0.035	-0.021
	(2.06)	(1.46)	(1.17)	(0.01)	(-0.30)	(1.84)	(1.06)	(-0.55)
Prime Base Rate_t	-0.056*	-0.050	-0.061*	-0.007	-0.011	-0.046	-0.041	-0.008
	(-1.66)	(-1.50)	(-1.73)	(-0.19)	(-0.25)	(-1.45)	(-1.29)	(-0.23)
$\text{Performance Pricing}_t$	-0.211***	-0.216***	-0.188***	-0.216***	-0.190***	-0.221***	-0.225***	-0.187***
	(-6.73)	(-6.73)	(-5.76)	(-6.53)	(-5.78)	(-7.62)	(-8.05)	(-6.35)
$\text{Log(Total Assets)}_{t-1}$	0.024	0.022	0.017	0.015	0.011	0.015	0.013	-0.038
	(1.55)	(1.55)	(1.14)	(0.28)	(0.19)	(1.16)	(1.11)	(-0.74)
Coverage_{t-1}	-0.001**	-0.001**	-0.001***	-0.001	-0.002	-0.001**	-0.001**	-0.002
	(-2.32)	(-2.40)	(-2.65)	(-0.98)	(-1.48)	(-2.29)	(-2.47)	(-1.27)
Leverage_{t-1}	0.343***	0.334***	0.362***	0.436***	0.498***	0.365***	0.357***	0.406***
	(3.62)	(3.33)	(3.65)	(2.85)	(3.46)	(3.64)	(4.70)	(3.06)
$\text{Profitability}_{t-1}$	-0.120	-0.133	-0.189	-0.547*	-0.536	-0.129	-0.189	-0.594*
	(-0.88)	(-1.05)	(-1.42)	(-1.83)	(-1.61)	(-0.95)	(-1.28)	(-1.78)
Tangibility_{t-1}	0.082	0.087	0.087	-0.125	0.014	0.099	0.089	-0.032
	(1.03)	(1.12)	(1.17)	(-0.59)	(0.07)	(1.29)	(1.23)	(-0.15)
$\text{Current Ratio}_{t-1}$	0.008	0.012	0.014	-0.029	-0.035	0.024	0.018	-0.034
	(0.22)	(0.34)	(0.37)	(-0.57)	(-0.58)	(0.60)	(0.45)	(-0.56)
$\text{Market-to-Book}_{t-1}$	-0.051***	-0.048**	-0.038*	-0.085***	-0.055**	-0.054***	-0.050**	-0.054***
	(-2.75)	(-2.47)	(-1.84)	(-3.39)	(-2.15)	(-2.84)	(-2.43)	(-2.76)
Rating FE	Yes	Yes	Yes	No	No	Yes	Yes	No
Industry FE	Yes	No	No	No	No	Yes	No	No
Year FE	Yes	No	No	No	No	Yes	No	No
Loan Type FE	Yes	Yes	No	Yes	No	Yes	Yes	No
Loan Purpose FE	Yes	Yes	No	Yes	No	Yes	Yes	No
Industry x Year FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Loan Type x Year FE	No	No	Yes	No	Yes	No	No	Yes
Loan Purpose x Year FE	No	No	Yes	No	Yes	No	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No	Yes
Observations	2,278	2,269	2,217	2,194	2,140	2,133	2,124	1,991
Adjusted R^2	0.855	0.862	0.872	0.882	0.894	0.860	0.867	0.896
Cluster Variable	Firm	Firm	Firm	Firm	Firm	State	State	State
Number of Clusters	394	392	388	311	307	42	42	38

Table 3: Borrower Prestige and Different Financing Cost Components

This table provides results of linear regressions of individual components of the total cost of borrowing on lagged prestige score and control variables. Panel A shows the results for the all-in-spread-drawn (AISD), the all-in-spread-undrawn (AISU), and the interest rate spread over LIBOR. Panel B shows the results for upfront fees, commitment fees, and facility fees. All dependent variables are log-transformed. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Alternative Measures for the Cost of Borrowing

	Log(AISD)		Log(AISU)		Log(Spread)	
	(1)	(2)	(3)	(4)	(5)	(6)
Prestige$_{t-1}$	-0.163***	-0.078***	-0.119***	-0.066***	-0.173***	-0.088***
	(-4.47)	(-3.53)	(-4.79)	(-4.13)	(-4.21)	(-3.72)
Loan Features	No	Yes	No	Yes	No	Yes
Borrower Characteristics	No	Yes	No	Yes	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes
Loan Purpose FE	No	Yes	No	Yes	No	Yes
Observations	3,239	3,232	2,375	2,366	2,974	2,968
Adjusted R^2	0.438	0.744	0.507	0.763	0.469	0.778
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	504	503	469	466	481	480

Panel B: Fee Types

	Log(Upfront Fee)		Log(Commitment Fee)		Log(Facility Fee)	
	(1)	(2)	(3)	(4)	(5)	(6)
Prestige$_{t-1}$	-0.157*	-0.113**	-0.080*	-0.025	-0.102***	-0.048***
	(-1.96)	(-2.11)	(-1.75)	(-0.81)	(-4.97)	(-3.18)
Loan Features	No	Yes	No	Yes	No	Yes
Borrower Characteristics	No	Yes	No	Yes	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes
Loan Purpose FE	No	Yes	No	Yes	No	Yes
Observations	812	801	956	950	1,688	1,678
Adjusted R^2	0.159	0.581	0.279	0.592	0.525	0.742
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	254	252	324	323	335	332

Table 4: Impact of Borrower Prestige on Pricing of Credit Lines and Term Loans
This table provides results of linear regressions of the total cost of borrowing (TCB), and the three most commonly used fee types – spread over LIBOR, facility, and upfront fee – on prestige score and the a credit line dummy. We only look at loans that can be classified as either credit line or term loans. Including the loan type fixed effects leads to omission of the credit line dummy in columns (2), (4), (6), and (8). All dependent variables are log-transformed. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses for the top three rows of controls. We report values of the F-test of the null of zero in the fourth row. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(TCB)		Log(Loan Spread)		Log(Facility Fee)		Log(Upfront Fee)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prestige_{t-1}	-0.056	0.006	-0.013	0.008	-0.005	0.022	0.047	0.041
	(-1.17)	(0.21)	(-0.24)	(0.21)	(-0.03)	(0.13)	(0.50)	(0.46)
Prestige * Credit Line	-0.112**	-0.070***	-0.210***	-0.121***	-0.105	-0.070	-0.280***	-0.197***
	(-2.27)	(-2.65)	(-4.04)	(-3.84)	(-0.64)	(-0.42)	(-3.24)	(-2.66)
Credit Line	-0.723**	-	0.379	-	0.234	-	0.936*	-
	(-2.59)		(1.29)		(0.21)		(1.87)	
Prestige + Prestige * Credit Line	-0.168***	-0.064***	-0.223***	-0.113***	-0.11***	-0.048***	-0.233***	-0.156***
	(46.80)	(16.72)	(49.07)	(22.19)	(28.26)	(9.85)	(8.82)	(9.39)
Loan Features	No	Yes	No	Yes	No	Yes	No	Yes
Borrower Characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Purpose FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2,278	2,274	2,785	2,781	1,641	1,636	737	729
Adjusted R^2	0.665	0.856	0.578	0.784	0.544	0.749	0.257	0.580
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	394	394	474	474	332	330	246	244

Table 5: Borrower Prestige and Credit Risk

This table provides results of linear regressions of measures of credit risk on borrower prestige and control variables. In columns (1) and (2), the dependent variable is the average S&P rating of a borrower over the loan maturity. In columns (3) and (4), the dependent variable is the average implied recovery from Markit CDS spreads of a borrower over the loan maturity. In columns (5) and (6), we use the average 5-year Markit CDS spread of a borrower over the loan maturity as a dependent variable. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	$\overline{\text{Rating}}$		$\overline{\text{Recovery}}$		$\overline{\text{CDS Spread}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Prestige$_{t-1}$	0.034	0.052	0.003	0.002	0.004	0.006
	(0.54)	(0.80)	(1.24)	(0.93)	(0.52)	(0.84)
Log(Spread)		0.374***		-0.004**		0.023**
		(4.18)		(-2.27)		(1.99)
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,660	2,590	993	781	991	779
Adjusted R^2	0.899	0.901	0.221	0.240	0.282	0.313
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	452	402	179	169	179	169

Table 6: Regression Discontinuity Analysis

This table presents non-parametric estimates for a regression discontinuity (RD) analysis with a kernel regression using a triangular kernel as implemented by Calonico et al. (2017). We report two different models – conventional RD estimates with conventional variance estimator (Conventional), and bias-corrected RD estimates with robust variance estimator (Robust). A sharp RD design is assumed in which the treatment variable – ranking in *Fortune Magazine's Most Admired Companies* – jumps from one to zero at rank 100. We run the analysis for all firms ranked between 80 and 120 (Panel A) and a placebo test for a hypothetical cutoff set to 150 and all firms ranked between 130 and 170 (Panel B). In columns (1) and (3), we report results without including any covariates. In columns (2) and (4), we report results with the covariates facility amount, maturity, total assets, leverage and market-to-book. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Threshold Value of 100

	Log(TCB)		$\overline{\text{Rating}}$	
	(1)	(2)	(3)	(4)
Conventional	-0.638*	-0.825**	-3.091**	-0.167
	(-1.93)	(-2.17)	(-2.23)	(-0.18)
Robust	-0.709*	-1.008**	-3.811**	-0.633
	(-1.75)	(-2.14)	(-2.33)	(-0.59)
Observations	280	280	494	494

Panel B: Threshold Value of 150 (Placebo)

	Log(TCB)		$\overline{\text{Rating}}$	
	(1)	(2)	(3)	(4)
Conventional	1.883***	-0.177	-0.485	-1.435
	(2.84)	(-0.43)	(-0.33)	(-1.26)
Robust	2.342***	-0.258	-0.865	-1.500
	(2.99)	(-0.48)	(-0.50)	(-1.06)
Observations	197	197	402	402

Table 7: Covariate Imbalances Before and After Coarsened Exact Matching

This table reports measures of imbalance before and after applying the coarsened exact matching (CEM) algorithm of Iacus et al. (2012). $\mathcal{L}_1$ measures the unidimensional imbalance between firms ranked in the top hundred of Fortune Magazine's Most Admired Companies (treated) and firms that are not (untreated) where $\mathcal{L}_1$ is bounded between zero and one. A lower $\mathcal{L}_1$ statistic indicates lower imbalance. We also report differences in means and medians between treated and untreated groups. CEM (1) refers to matching on total assets and leverage. CEM (2) refers to matching on total assets, leverage, market-to-book, and coverage. Matching on all borrower characteristics does not yield enough observations for meaningful statistical inference. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1.

	Before CEM			After CEM (1)			After CEM (2)		
	$\mathcal{L}_1$	ΔMean	ΔMedian	$\mathcal{L}_1$	ΔMean	ΔMedian	$\mathcal{L}_1$	ΔMean	ΔMedian
Log(Total Assets)	0.711	3.011	3.110	0.548	1.687	1.894	0.400	1.016	0.060
Coverage	0.301	0.692	3.883	0.200	3.252	2.965	0.191	3.735	1.284
Leverage	0.291	-0.076	-0.074	0.209	-0.024	-0.039	0.221	-0.035	-0.047
Profitability	0.183	0.023	0.024	0.120	0.005	0.010	0.130	-0.013	-0.007
Tangibility	0.217	0.004	0.020	0.205	-0.014	-0.003	0.163	-0.023	-0.021
Current Ratio	0.123	-0.054	0.006	0.123	-0.021	0.006	0.132	-0.020	-0.006
Market-to-Book	0.257	0.452	0.271	0.245	0.475	0.283	0.220	0.275	0.132

Table 8: Matched Sample Regressions

This table provides results of linear regressions of the total cost of borrowing (TCB) and the average borrower rating over loan maturity on a dummy variable indicating whether a company is ranked among the top 100 companies in *Fortune Magazine's Most Admired Companies* and control variables. Columns (1) and (4) show the results without applying any matching algorithm. In columns (2) and (5), we apply the coarsened exact matching (CEM) algorithm of Iacus et al. (2012) on borrowers' total assets and leverage to reduce the imbalance between observations which are among the top 100 companies (treated) and those that are not (untreated). In columns (3) and (6), we match on total assets, leverage, market-to-book, and coverage. Matching on all borrower characteristics does not yield enough observations for meaningful statistical inference. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(TCB)			$\overline{\text{Rating}}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Top 100_{t-1}	-0.021	-0.081***	-0.085***	0.092	-0.011	0.049
	(-0.75)	(-3.26)	(-3.39)	(0.83)	(-0.10)	(0.56)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,864	9,989	5,012	10,531	7,315	4,227
Adjusted R^2	0.835	0.855	0.850	0.912	0.895	0.905
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	3,842	1,772	1,010	1,583	1,149	814

Table 9: Average Treatment Effect for Alternative Matching Estimators

This table provides matching results for different set of control variables and numbers of neighbors. The variable of interest is the average treatment effect on the treated of firms ranked among the top 100 most admired companies. In Panel A, we apply nearest neighbor matching including the bias-adjustment of Abadie and Imbens (2006, 2011) to correct for the bias that arises due to the use of continuous control variables. In Panel B, we apply propensity score matching including standard errors derived in Abadie and Imbens (2016) to account for the fact that the propensity score is an estimated quantity. We use a probit model to estimate propensity scores. We drop observations if they violate the overlap assumption for a specific model. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1.

Panel A: Nearest Neighbor Matching

	Log(TCB)			
	(1)	(2)	(3)	(4)
Top 100_{t-1}	-0.121**	-0.065**	-0.237***	-0.095***
	(-2.17)	(-2.22)	(-7.20)	(-4.31)
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Features	No	Yes	No	Yes
Neighbors	1	1	10	10
Observations	22,207	19,752	22,207	17,064

Panel B: Propensity Score Matching

	Log(TCB)			
	(1)	(2)	(3)	(4)
Top 100_{t-1}	-0.339***	-0.251***	-0.476***	-0.243***
	(-6.67)	(-5.12)	(-12.14)	(-6.81)
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Features	No	Yes	No	Yes
Neighbors	1	1	10	10
Observations	22,207	22,207	22,207	22,207

Table 10: Borrower Prestige and Bank Competition

This table provides results for linear regressions with measures of competition. In columns (1) and (2) we regress syndicate size (i.e. the number of participants in a deal) on borrower prestige and lead share (i.e. percentage of loan retained the lead arranger at loan origination). In columns (3) and (4), we regress the lead share on borrower prestige and syndicate size. In columns (5)-(8), the dependent variable is the total cost of borrowing (TCB). The sample is based on loans in the US syndicated loan market between 1982 and 2009. For each deal in the sample, we select the the largest facility to represent the deal. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Syndicate Size		Lead Share		Log(TCB)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prestige_{t-1}	1.143***	0.885**	4.183*	2.645**	-0.061	0.010	-0.069	-0.063*
	(2.66)	(2.06)	(1.96)	(2.29)	(-1.23)	(0.48)	(-1.17)	(-1.82)
Prestige * Syndicate Size					-0.003	-0.003***		
					(-1.49)	(-2.78)		
Syndicate Size			-1.268***	-0.432***	0.010	0.012**		
			(-6.39)	(-3.65)	(0.75)	(2.04)		
Lead Share	-0.249***	-0.092***					0.036***	0.006
	(-16.34)	(-4.36)					(4.56)	(0.84)
Prestige * Lead Share							-0.005***	-0.001
							(-3.71)	(-0.98)
Loan Features	No	Yes	No	Yes	No	Yes	No	Yes
Borrower Characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Purpose FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	698	694	698	694	1,651	1,645	521	515
Adjusted R^2	0.359	0.580	0.400	0.639	0.415	0.824	0.373	0.825
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	266	266	266	266	389	388	211	211

Table 11: Borrower Prestige and Lending Relationships

This table provides results for linear regressions of measures of loan pricing on borrower prestige and control variables with a focus on bank relationship variables. The dependent variable is either the total cost of borrowing (TCB) in columns (1)-(4) or the upfront fee in columns (5)-(8). The key explanatory variables are the interaction terms of lagged prestige score with variables related to the relationship between a borrower and a lender. In columns (1) and (5), the relevant variable is a dummy which indicates whether a borrower and a lender interact for the first time in a given deal (New Relation). In columns (2) and (6), the relevant variable is a dummy which indicates whether a borrower and a lender interacted in the last five years before a deal (Old Relation (Dummy)). In columns (3) and (7), we use the share of the number of loans between a borrower and a lender as a fraction of the total number of loans of a borrower in the last five years before a deal (Old Relation (Number)). In columns (4) and (8), we use the share of the loan amount between a borrower and a lender as a fraction of the total loan amount of a borrower in the last five years before a deal (Old Relation (Amount)). The sample is based on loans in the US syndicated loan market between 1982 and 2009. For each deal in the sample, we select the the largest facility to represent the deal. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(TCB)				Log(Upfront Fee)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prestige * New Relation	-0.026				-0.287**			
	(-1.04)				(-2.54)			
Prestige * Old Relation (Dummy)		0.021				0.238**		
		(0.85)				(2.13)		
Prestige * Old Relation (Number)			0.006				0.358**	
			(0.19)				(2.02)	
Prestige * Old Relation (Amount)				-0.001				0.197
				(-0.03)				(1.18)
Prestige_{t-1}	-0.026	-0.049**	-0.034	-0.032	-0.102	-0.337***	-0.308***	-0.260**
	(-1.60)	(-2.00)	(-1.46)	(-1.32)	(-1.12)	(-3.55)	(-2.91)	(-2.39)
New Relation	0.172				1.911***			
	(1.07)				(2.77)			
Old Relation (Dummy)		-0.138				-1.616**		
		(-0.86)				(-2.35)		
Old Relation (Number)			-0.040				-2.144**	
			(-0.19)				(-2.02)	
Old Relation (Amount)				-0.009				-1.207
				(-0.04)				(-1.20)
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,236	1,236	1,168	1,168	222	222	191	191
Adjusted R^2	0.842	0.842	0.848	0.848	0.580	0.576	0.523	0.515
Cluster Variable	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of Clusters	337	337	320	320	153	153	133	133

Table 12: Descriptive Statistics for Bank-Level Sample

This table reports descriptive statistics for variables used in the bank level analysis. For each variable, the number of observations (N), mean, standard deviation (SD), 10% quantile ($Q_{0.10}$), 25% quantile ($Q_{0.25}$), median ($Q_{0.50}$), 75% quantile ($Q_{0.75}$), and 99% quantile ($Q_{0.99}$) are reported. Loan volume, loan number, average loan volume and the number of unique borrowers are based on aggregating deals from *Dealscan* to an annual level. Top 100 loans refers to the number of loans originated for companies ranked among the top 100 companies according to *Fortune's Most Admired Companies* surveys. The remaining bank characteristics are collected from *Compustat*. The panel of yearly bank level observations spans from 1982 to 2009. We define all variables in Table A1.

	N	Mean	SD	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
Loan Volume [USD bn.]	1,187	6.05	20.63	0.02	0.08	0.54	3.33	12.07
Loan Number	1,187	17.68	34.85	1.00	2.00	6.00	18.00	38.00
Average Loan Volume [USD mn.]	1,187	210.42	493.67	10.00	25.00	82.50	234.64	497.63
Unique Borrowers [number]	1,187	16.21	31.56	1.00	2.00	6.00	16.00	36.00
Top 100 Loans [number]	1,187	0.69	2.42	0.00	0.00	0.00	0.00	2.00
Total Assets [USD bn.]	946	227.13	442.66	9.46	21.82	58.62	219.23	632.57
Market-to-Book [number]	862	1.06	0.07	0.99	1.01	1.04	1.09	1.14
Deposits/Assets [number]	946	0.67	0.13	0.55	0.62	0.68	0.75	0.80
Tier 1 Ratio [0-100]	596	8.82	1.80	7.10	7.68	8.44	9.54	10.92

Table 13: Bank-Level Regressions

This table provides results for linear regressions of lead arrangers' business activities on a measure that captures the lending to prestigious borrowers and control variables. The dependent variable is the future loan volume in columns (1) and (2), average volume per loan in columns (3) and (4), the number of loans underwritten in columns (5) and (6), and the number of unique borrowers in columns (7) and (8). The key explanatory variable is the Log(1+ Top 100 Loans) variable which is based on *Fortune' Most Admired Companies* survey. In all regression specification, we include bank and year fixed effects. Depending on the column, we also control for the bank's total assets, market-to-book ratio and deposits over assets ratio. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The main results are displayed in Panel A. Panel B shows the results for up to 5 lags in the key explanatory variable. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and bank characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the bank level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Main Bank-Level Analysis

	Log(Volume)_t		$\text{Log}\left(\frac{\text{Volume}}{\text{Loans}}\right)_t$		Log(Loans)_t		Log(Borrowers)_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Log(1 + Top 100 Loans)}_{t-1}$	0.483***	0.296**	0.076	-0.059	0.407***	0.355***	0.382***	0.333***
	(4.21)	(2.13)	(0.85)	(-0.50)	(7.15)	(6.17)	(6.49)	(5.85)
$\text{Log(Total Assets)}_{t-1}$		1.044***		0.363***		0.681***		0.675***
		(4.03)		(2.87)		(4.39)		(4.34)
$\text{Market-to-Book}_{t-1}$		-1.193		-1.356**		0.163		0.037
		(-1.18)		(-2.13)		(0.23)		(0.05)
$\text{Deposit/Assets}_{t-1}$		1.320		-0.073		1.392**		1.317**
		(1.30)		(-0.10)		(2.38)		(2.27)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186	860	1,186	860	1,186	860	1,186	860
Adjusted R^2	0.772	0.815	0.688	0.696	0.766	0.810	0.770	0.814
Cluster Variable	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Clusters	100	75	100	75	100	75	100	75

Panel B: Bank-Level Analysis With Additional Lags

	Log(Volume)_t		$\text{Log}\left(\frac{\text{Volume}}{\text{Loans}}\right)_t$		Log(Loans)_t		Log(Borrowers)_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Log(1 + Top 100 Loans)}_{t-1}$	0.456***	0.187*	0.079	-0.063	0.377***	0.249***	0.347***	0.234***
	(3.61)	(1.70)	(1.01)	(-0.77)	(5.06)	(4.41)	(4.51)	(4.08)
$\text{Log(1 + Top 100 Loans)}_{t-2}$	0.258***	0.231**	0.133**	0.099*	0.125**	0.131**	0.126***	0.120**
	(3.16)	(2.46)	(2.39)	(1.68)	(2.58)	(2.45)	(2.64)	(2.32)
$\text{Log(1 + Top 100 Loans)}_{t-3}$	-0.132	0.137	-0.061	0.041	-0.071	0.096	-0.063	0.092
	(-1.06)	(1.50)	(-0.89)	(0.61)	(-0.95)	(1.60)	(-0.90)	(1.62)
$\text{Log(1 + Top 100 Loans)}_{t-4}$	-0.011	-0.034	-0.041	-0.078	0.030	0.044	0.032	0.039
	(-0.09)	(-0.31)	(-0.53)	(-1.24)	(0.44)	(0.60)	(0.50)	(0.55)
$\text{Log(1 + Top 100 Loans)}_{t-5}$	-0.106	-0.099	-0.091	-0.111	-0.015	0.013	-0.010	0.014
	(-0.75)	(-0.75)	(-1.10)	(-1.37)	(-0.20)	(0.19)	(-0.14)	(0.22)
$\text{Log(Total Assets)}_{t-1}$		1.026***		0.367***		0.660***		0.655***
		(3.97)		(2.85)		(4.30)		(4.26)
$\text{Market-to-Book}_{t-1}$		-1.152		-1.369**		0.217		0.086
		(-1.14)		(-2.09)		(0.31)		(0.12)
$\text{Deposit/Assets}_{t-1}$		1.411		-0.111		1.521**		1.438**
		(1.33)		(-0.15)		(2.60)		(2.49)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186	860	1,186	860	1,186	860	1,186	860
Adjusted R^2	0.772	0.815	0.688	0.696	0.766	0.812	0.770	0.815
Cluster Variable	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Clusters	100	75	100	75	100	75	100	75

Figures

Figure 1: U.S. Syndicated Loan Credentials

This figure illustrates the common practice of banks using loans with prestigious borrowers as a marketing tool to win future business (credentials). The graph shows US syndicated loan credentials that Royal Bank of Canada (RBC) used in client presentations in 2009.

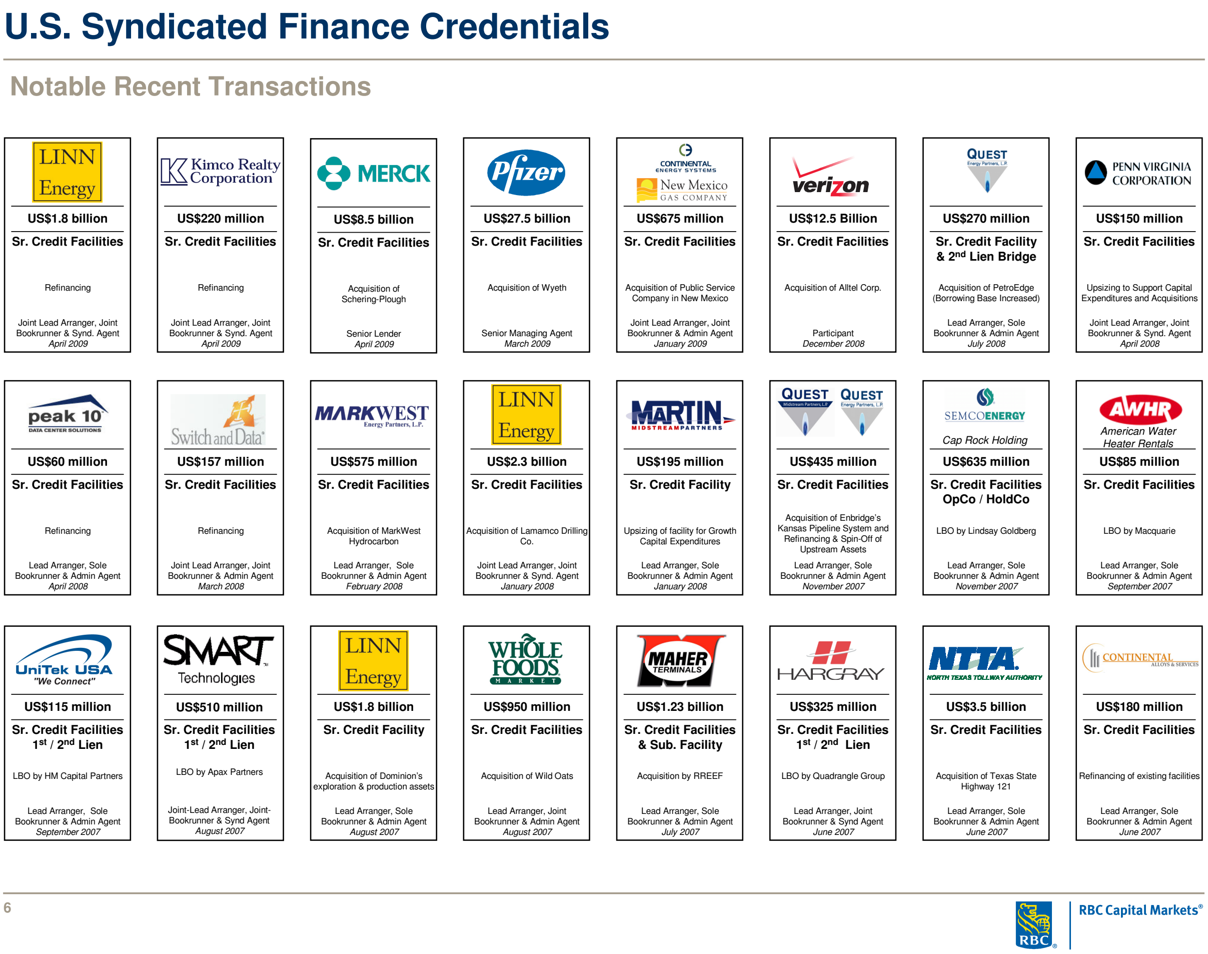


Figure 2: European Syndicated Loan Credentials

This figure illustrates the common practice of banks using loans with prestigious borrowers as a marketing tool to win future business (credentials). The graph shows European syndicated loan credentials for UniCredit in 2013.

Figure 3: Distribution of Borrower Prestige

This histogram shows the distribution of the prestige score from *Fortune's Most Admired Companies* surveys between 1982 and 2009 for borrower with loan data in *Dealscan*. The horizontal axis reports the prestige score which can take any value between zero and ten. The vertical axis shows the frequency of the respective bin in percent. The prestige data is manually collected from printed editions of *Fortune Magazine*.

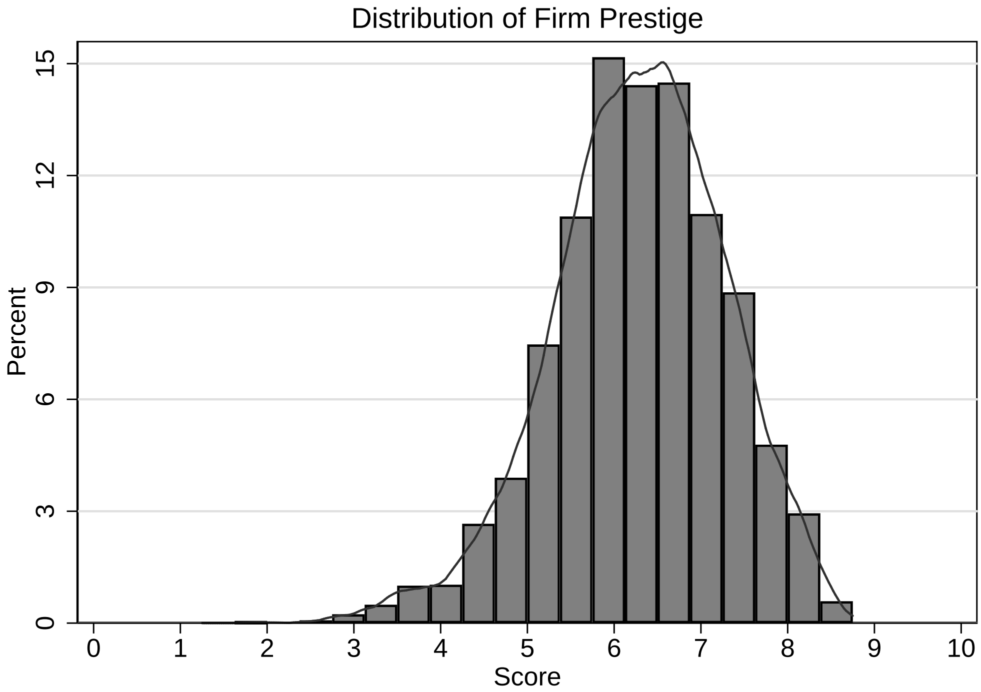


Figure 4: Borrower Prestige and the Cost of Borrowing

These figures illustrate the strong negative relationship between borrower prestige and the cost of borrowing. The scatter plot in the top shows the relation for the total cost of borrowing (TCB) of Berg et al. (2016). The graph in the middle illustrates the relationship for the loan spread over LIBOR. The bottom plot shows the relation for upfront fees. In all plots, the horizontal axis reports the prestige score, which can take any value between zero and ten. The solid lines represent fitted values from an OLS regressions. Loan spreads and upfront fees are obtained from *Dealscan* and the prestige score is manually collected from printed editions of *Fortune Magazine*. The sample covers the time period 1982 to 2009.

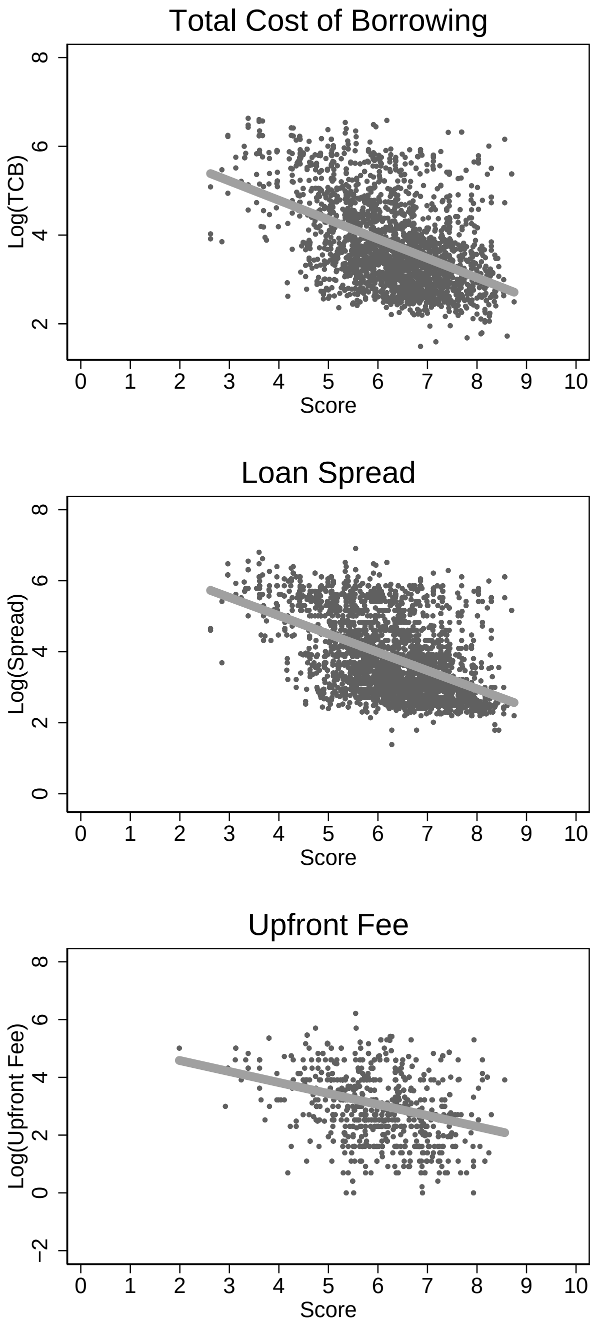
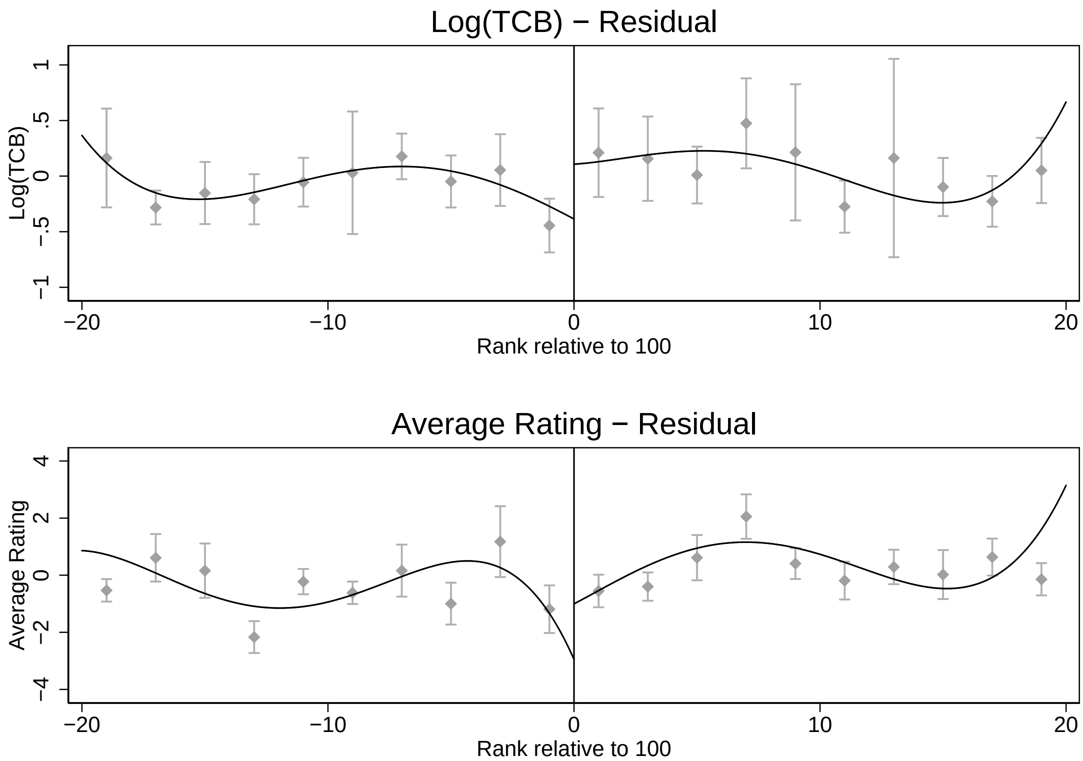


Figure 5: Regression Discontinuity around Rank 100 of Prestige Survey

This figure shows non-parametric estimates of two local polynomial regressions using a triangular kernel as implemented by Calonico et al. (2015). The dependent variables are the residuals of the regression of the total cost of borrowing (TCB) and the average rating over loan maturity on facility amount, maturity, total assets, leverage and market-to-book. The cutoff equals rank 100 in *Fortunes' Most Admired Companies* survey. We only consider companies with ranks between 80 and 120. In both charts, the horizontal axis reports the rank based on the prestige score as reported in the survey. The vertical lines represent 90% confidence intervals for each bin. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1.



A Appendix

Table A1: Variable Definitions and Data Sources

Variable [Units]	**Source**	**Definition**
Prestige Variables		
Prestige [0-10]	Fortune	Prestige score of the borrower as defined by *Fortune's Most Admired Companies* survey.
Top 100 [0/1]	Fortune	Dummy variable equal to one if the borrower is ranked among the top 100 firms in the *Fortune's Most Admired Companies* survey (by score).
Loan Characteristics		
TCB [bps]	Dealscan	Total Cost of Borrowing (TCB) developed and provided by Berg et al. (2016). The TCB measure reflects option characteristics of loans, differentiates between credit lines and term loans, and takes various fees paid to lenders into account.
AISD [bps]	Dealscan	All-in-spread-drawn, defined as the sum of the spread over LIBOR plus the facility fee.
AISU [bps]	Dealscan	All-in-spread-undrawn, defined as the sum of the facility fee and the commitment fee.
Spread [bps]	Dealscan	Spread over LIBOR paid on drawn amounts on credit lines.
Upfront Fee [bps]	Dealscan	Fee paid upon completion of syndicated loan deal.
Commitment Fee [bps]	Dealscan	Fee paid on the unused amount of loan commitments.
Facility Fee [bps]	Dealscan	Fee paid on the total committed amount independent of usage.
Amount [USD mn.]	Dealscan	Facility amount as indicated in the field *FacilityAmt* in the Dealscan facility table.
Maturity [months]	Dealscan	Facility maturity in months as indicated in the field *Maturity* in the Dealscan facility table.
Facilities [number]	Dealscan	Number of facilities in a package.
Secured [0/1]	Dealscan	Dummy variable equal to one if facility is secured as indicated by the field *Secured* in the Dealscan facility table.
Financial Covenants [0/1]	Dealscan	Dummy variable equal to one if the loan has financial covenants as indicated by appearing the Dealscan financial covenants table.
Prime Base Rate [0/1]	Dealscan	Dummy variable equal to one if the base rate is prime as indicated by the field *Baserate* in the Dealscan current facility pricing table.
Performance Pricing [0/1]	Dealscan	Dummy variable equal to one if the loan has performance pricing as indicated by appearing in the Dealscan performance pricing table.
Credit Line [0/1]	Dealscan	Loans with type "364-Day Facility", "Revolver/line < 1 Yr.", "Revolver/Line >= 1 Yr.", or "Revolver/Term Loan" as indicated in the field *Loantype* in the Dealscan facility table.
Term Loan [0/1]	Dealscan	Loans with type "Term Loan", "Term Loan A"-"Term Loan K", and "Delay Draw Term Loan" as indicated in the field *Loantype* in the Dealscan facility table.
Syndicate Size [number]	Dealscan	Number of lenders (lead arranger and participants) of a syndicated loan facility as indicated by the Dealscan lender shares table.
Lead Share [0-1]	Dealscan	Share of the loan that is retained by the lead bank at loan origination as indicated by the field *BankAllocation* in the Dealscan lender shares table.

New Relation [0/1]	Dealscan	Dummy variable equal to one if the lead banks lends to the borrower for the first time. The variable is set to missing for the first loan of each company in our sample.
Old Relation (Dummy) [0/1]	Dealscan	Dummy variable equal to one if the borrower and lender had at least one lending relationship in the last 5 years before loan origination.
Old Relation (Number) [0-1]	Dealscan	Number of loans by bank j to borrower i in the last 5 years before loan origination divided by the total number of loans by borrower i in the last 5 years.
Old Relation (Amount) [0-1]	Dealscan	Amount of loans by bank j to borrower i in the last 5 years before loan origination divided by the total amount of loans by borrower i in the last 5 years.
$\overline{\text{Rating}}$ [1-15]	Compustat	Average S&P rating over loan maturity.
$\overline{\text{Recovery}}$ [number]	Markit	Average implied recovery over loan maturity.
$\overline{\text{CDS Spread}}$ [number]	Markit	Average 5-year CDS spread over loan maturity.
Borrower Characteristics		
Total Assets [number]	Compustat	Total book assets (*at*) in USD million.
Coverage [number]	Compustat	Ratio of EBITDA (*ebitda*) to interest expenses (*xint*).
Leverage [number]	Compustat	Ratio of book value of total debt (*dltt* + *dlc*) to book value of assets (*at*).
Profitability [number]	Compustat	Ratio of EBITDA (*ebitda*) to sales (*sale*).
Tangibility [number]	Compustat	Ratio of property, plant, and equipment (*ppent*) to total assets (*at*).
Current Ratio [number]	Compustat	Ratio of current assets (*aco*) to current liabilities (*lco*).
Market-to-Book [number]	Compustat	Ratio of book value of assets (*at*) - book value of equity (*ceq*) + market value of equity (*csho**prcc_f*) to book value of assets (*at*).
Investment Grade [0/1]	Compustat	Dummy variable equal to one if the S&P rating is BBB- or higher and missing for non-rated borrowers.
Not Rated [0/1]	Compustat	Dummy variable equal to one if no S&P rating for the borrower exists.
Bank Level Variables		
Loan Volume [USD bn.]	Dealscan	Total volume of all loans underwritten by lead bank in a given year.
Loans [number]	Dealscan	Total number of loans underwritten by lead bank in a given year.
Loans / Volume [number]	Dealscan	Average loan volume issued by lead bank in a given year.
Unique Borrowers [number]	Dealscan	Number of unique borrowers that the lead bank provided with loans during the year.
Top 100 Loans [number]	Dealscan	Number of loans underwritten for borrowers that are ranked among the top 100 firms in the *Fortune's Most Admired Companies* survey.
Total Assets [USD bn.]	Compustat	Total book assets (*at*).
Market-to-Book [number]	Compustat	Ratio of book value of assets (*at*) - book value of equity (*ceq*) + market value of equity (*csho**price*) to book value of assets (*at*) where *price* is the month-end price from CRSP at the fiscal-year end.
Deposits/Assets [number]	Compustat	Deposits (*dptc*) over total assets (*at*).
Tier 1 Ratio [0-100]	Compustat	Risk-adjusted tier 1 capital ratio (*capr1*).

Internet Appendix to

Fishing with Pearls: The Value of Lending Relationships with Prestigious Firms

Alexander Mürmann Thomas Rauter Christoph Scheuch

Table of Contents

A Robustness Tests for Credit Risk Regressions

Table IA1: Borrower Prestige and Credit Risk at Loan Maturity

This table provides results of linear regressions of measures of credit risk on borrower prestige and control variables. In Panel A, the dependent variables describe credit risk at maturity. In columns (1) and (2), the dependent variable is the S&P rating of a borrower at loan maturity. In columns (3) and (4), the dependent variable is the implied recovery from Markit CDS spreads of a borrower at loan maturity. In columns (5) and (6), we use the 5-year Markit CDS spread of a borrower at loan maturity as a dependent variable. In panel B, we use the changes in these variables from origination to maturity as dependent variables. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and borrower characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the firm level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Credit Risk at Maturity

	Rating_m		Recovery_m		CDS Spread_m	
	(1)	(2)	(3)	(4)	(5)	(6)
Prestige_{t-1}	0.065	0.081	0.003	0.001	-0.001	-0.000
	(0.52)	(0.66)	(1.20)	(0.62)	(-0.68)	(-0.20)
Log(Spread)		0.524***		-0.008**		0.006**
		(3.41)		(-2.17)		(2.38)
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3626	2555	811	640	804	634
Adjusted R^2	0.725	0.731	0.224	0.302	0.381	0.376
Cluster Variable	bgvkey	bgvkey	bgvkey	bgvkey	bgvkey	bgvkey
Number of Clusters	454	411	164	154	162	152

Panel B: Changes in Credit Risk

	ΔRating		ΔRecovery		ΔCDS Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Score_{t-1}	0.094	0.104	-0.003	-0.004*	-0.001	-0.002
	(0.76)	(0.85)	(-1.65)	(-1.91)	(-0.88)	(-1.43)
Log(Spread)		0.501***		0.002		-0.009***
		(3.21)		(0.59)		(-2.76)
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3492	2474	639	482	629	474
Adjusted R^2	0.312	0.358	0.539	0.599	0.463	0.529
Cluster Variable	bgvkey	bgvkey	bgvkey	bgvkey	bgvkey	bgvkey
Number of Clusters	439	392	112	103	110	101

B Robustness Tests for Bank-Level Analyses

Table IA2: Baseline Regressions with Additional Controls

This table provides results for linear regressions of lead arrangers' business activities on a measure that captures the lending to prestigious borrowers and control variables. The dependent variable is the future loan volume in columns (1) and (2), average volume per loan in columns (3) and (4), the number of loans underwritten in columns (5) and (6), and the number of unique borrowers in columns (7) and (8). The key explanatory variable is the Log(1+ Top 100 Loans) variable which is based on *Fortune' Most Admired Companies* survey. In all regression specification, we include bank and year fixed effects. Depending on the column, we also control for the bank's total assets, market-to-book ratio, deposits over assets, and the tier 1 capital ratio. The sample is based on loans in the US syndicated loan market between 1982 and 2009. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and bank characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the bank level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(Volume)_t		$\text{Log}\left(\frac{\text{Volume}}{\text{Loans}}\right)_t$		Log(Loans)_t		Log(Borrowers)_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(1 + Top 100 Loans)$_{t-1}$	0.483***	0.245*	0.076	-0.012	0.407***	0.257***	0.382***	0.242***
	(4.21)	(1.88)	(0.85)	(-0.14)	(7.15)	(4.18)	(6.49)	(3.96)
Log(Total Assets)$_{t-1}$		0.722**		0.230		0.492***		0.494***
		(2.25)		(1.36)		(2.77)		(2.82)
Market-to-Book$_{t-1}$		-0.630		-1.346**		0.717		0.703
		(-0.67)		(-2.61)		(1.02)		(1.02)
Deposit/Assets$_{t-1}$		0.471		-0.718		1.189*		1.183*
		(0.44)		(-0.98)		(1.86)		(1.93)
Tier 1 Ratio$_{t-1}$		-0.039		0.002		-0.041		-0.047
		(-0.79)		(0.08)		(-1.03)		(-1.22)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186	542	1,186	542	1,186	542	1,186	542
Adjusted R^2	0.772	0.857	0.688	0.750	0.766	0.855	0.770	0.859
Cluster Variable	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Clusters	100	66	100	66	100	66	100	66

Table IA3: Baseline Specification with Longer Lag Structure

This table provides results for linear regressions of lead arrangers' business activities on a measure that captures the lending to prestigious borrowers and control variables. The dependent variable is the future loan volume in columns (1) and (2), average volume per loan in columns (3) and (4), the number of loans underwritten in columns (5) and (6), and the number of unique borrowers in columns (7) and (8). The key explanatory variable is the Log(1+ Top 100 Loans) variable which is based on *Fortune' Most Admired Companies* survey. In all regression specification, we include bank and year fixed effects. Depending on the column, we also control for the bank's total assets, market-to-book ratio, deposits over assets, and the tier 1 capital ratio. The sample is based on loans in the US syndicated loan market between 1982 and 2009. This table shows the results for up to 5 lags in the key explanatory variable. The prestige data is manually collected from printed editions of *Fortune Magazine*, loan and bank characteristics are obtained from *Dealscan* and *Compustat*, respectively. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the bank level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Log(Volume)_t		$\text{Log}\left(\frac{\text{Volume}}{\text{Loans}}\right)_t$		Log(Loans)_t		Log(Borrowers)_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Log(1 + Top 100 Loans)}_{t-1}$	0.456***	0.202*	0.079	-0.031	0.377***	0.232***	0.347***	0.220***
	(3.61)	(1.68)	(1.01)	(-0.41)	(5.06)	(3.55)	(4.51)	(3.33)
$\text{Log(1 + Top 100 Loans)}_{t-2}$	0.258***	0.122	0.133**	0.090	0.125**	0.032	0.126***	0.022
	(3.16)	(1.59)	(2.39)	(1.63)	(2.58)	(0.61)	(2.64)	(0.40)
$\text{Log(1 + Top 100 Loans)}_{t-3}$	-0.132	0.087	-0.061	0.028	-0.071	0.059	-0.063	0.053
	(-1.06)	(0.79)	(-0.89)	(0.36)	(-0.95)	(0.84)	(-0.90)	(0.80)
$\text{Log(1 + Top 100 Loans)}_{t-4}$	-0.011	0.000	-0.041	-0.005	0.030	0.006	0.032	0.007
	(-0.09)	(0.00)	(-0.53)	(-0.09)	(0.44)	(0.07)	(0.50)	(0.08)
$\text{Log(1 + Top 100 Loans)}_{t-5}$	-0.106	-0.065	-0.091	-0.084	-0.015	0.019	-0.010	0.028
	(-0.75)	(-0.46)	(-1.10)	(-0.99)	(-0.20)	(0.26)	(-0.14)	(0.40)
$\text{Log(Total Assets)}_{t-1}$		0.712**		0.230		0.482***		0.484***
		(2.18)		(1.32)		(2.70)		(2.75)
$\text{Market-to-Book}_{t-1}$		-0.623		-1.328**		0.705		0.691
		(-0.66)		(-2.52)		(1.01)		(1.01)
$\text{Deposit/Assets}_{t-1}$		0.468		-0.711		1.179*		1.173*
		(0.43)		(-0.96)		(1.85)		(1.93)
$\text{Tier 1 Ratio}_{t-1}$		-0.043		0.002		-0.045		-0.050
		(-0.89)		(0.07)		(-1.11)		(-1.30)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186	542	1,186	542	1,186	542	1,186	542
Adjusted R^2	0.772	0.856	0.688	0.748	0.766	0.854	0.770	0.858
Cluster Variable	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Clusters	100	66	100	66	100	66	100	66