Risk-mitigating effects of being prompt and transparent

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Abstract: We study risk-taking by banks in response to U.S. policy rates and potential mitigants of such risk-taking. We combine data on global originations of syndicated U.S. dollar term loans, borrowers of such loans, and micro- and macroprudential measures and market discipline that banks face. We find that certain microprudential tools—in particular, bank supervisors' prompt corrective power—dampen the supply of risky loans by banks in response to a monetary policy easing, with nonbanks making up some of the lost supply. Prompt corrective power is effective because it allows supervisors to timely force banks to cease risky lending and suspend capital disbursement. We also find that market discipline—specifically, banks' reporting transparency—have dampening effects too. In contrast, capital-related macroprudential tools have no mitigating effects, likely in part because banks quickly sell shares in syndicated loans after origination. We conclude that local supervisory powers and reporting transparency may have global "macroprudential" effects.

Keywords: Syndicated loans; global risk-taking channel of monetary policy; U.S. monetary policy; micro- and macroprudential tools; market discipline; prudential leakages. JEL

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1 Introduction

In the aftermath of the Global Financial Crisis (GFC), record-low policy interest rates have sparked intense debates about their effects on the provision of risky corporate credit and associated financial stability risks. The debates mostly draw on two strands of the literature: The strand on a risk-taking channel of monetary policy (Jimenez, Ongena, Peydro, and Saurina (2014), Ioannidou, Ongena, and Peydro (2015), Dell'Ariccia, Laeven, and Suarez (2017), and others) and the strand on the effectiveness of micro- and macro-prudential tools and other mechanisms in mitigating the riskiness of banks or the riskiness of certain activities of banks (Delis and Staikouras (2011), Calem, Correa, and Lee (2019), and others).

The debates may benefit from a better understanding of the effects of monetary policy on risk-taking conditional on supervisory, regulatory, and market constraints that banks face. However, the the research on mitigants of a risk-taking channel of monetary policy is rather nascent, for example, Altavilla, Boucinha, Peydro, and Smets (2019) and, to a lesser extent, Maddaloni and Peydro (2011). The former paper uses credit registries from the euro area to analyze the implications of a one-time, recent tightening of supervision for banks' risk-taking behavior, and its mitigating effect of a risk-taking channel of the ECB's monetary policy.

In this paper, we study ex ante risk-taking by banks in the global market for syndicated U.S. dollar term loans in response to U.S. policy rates and potential mitigants of such risk-taking. We focus on the mitigating effects of micro- and macroprudential tools and of market discipline that banks faced in their headquarters countries over the two decades, which include the period of unconventional monetary policy in the United States. Taking full advantage of our data sources, we identify a global risk-taking channel of U.S. monetary policy, a set of micro- and macroprudential tools and forms of market discipline that dampen the supply of risky loans by banks in response to a monetary policy easing, and reasons for the effectiviness of certain tools and forms. We also check for prudential "leakages", with nonbanks potentially making up some of the lost supply.

Figuring out mitigants of risk-taking in response to lower policy rates in corporate loan markets is important for at least a few reasons. First, global primary market for U.S. dollar syndicated term loans is comparable in terms of size with the global primary market for U.S. dollar corporate bonds. Second, the majority of syndicated term loans are made to risky corporate borrowers. Third, the vast majority of syndicated term loans are originated by banks which quickly sell shares in these loans to shadow banks—institutional investors such as mutual funds or structured finance vehicles—and retain only modest shares. In this originate-to-distribute model, banks essentially accommodate other lenders' investment choices in response to lower U.S. policy rates. Thus, tools that mitigate risk-taking by banks also mitigate risk-taking by the financial system more broadly. Fourth, macroprudential tools at the disposal of central banks and other regulators to manage financial risks are not necessarily designed to deal with threats emanating from corporate loan markets.[1] Moreover, because sales of loan shares happen quickly, it is likely that many loans never

[1]See "Macroprudential regulators lack tools to address corporate debt risk: Knot", S&P Global Market Intelligence, October 18, 2019; the URL `https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/54849318`.

appear on bank balance sheets on reporting dates, potentially rendering certain types of regulation or monitoring ineffective.

For our analysis, we merge three well-known data sets: Refinitiv Loan Pricing Corporation DealScan for information on syndicated loans; Moody's Analytics CreditEdge for expected default frequencies (EDFs) of syndicated loan borrowers; and Barth, Caprio, and Levine (2013)' surveys of microprudential, macroprudential, private monitoring, and external governance tools that banks face in their headquarter countries. For completeness, we merge a data set from Cerutti, Correa, Fiorentino, and Segalla (2017) on the implementation of Basel III—an international accord on capital regulation—across countries. We end up with a global sample that covers banks and borrowers from a large number of countries, with loans made by U.S. banks to U.S. borrowers representing a significant but not dominant share of observations.

We design an identification approach that links amounts of risky loans with U.S. monetary policy and potential mitigants of risk-taking and deals with potential endogeneity-related biases in multiple ways. First, we study loan originations as in Dell'Ariccia, Laeven, and Suarez (2017) and others. Second, we exploit differences in characteristics of banks lending to the same borrowers, similar to Khwaja and Mian (2008)'s approach. Third, we identify the effects of interest through interaction terms (as in Kashyap and Stein (2000)). Fourth, we saturate regression models with fixed (time) effects to control for bank and borrower unobserved conditions.

To further dispel endogeneity concerns and strengthen the identification of the effects of U.S. monetary policy on global risk-taking, we estimate regression models on a sample that excludes U.S. borrowers. In this sub-sample, loans made by non-U.S. lenders to borrowers from emerging market economies represent a significant share of observations. Thus, we mimic the strategy of Jimenez, Ongena, Peydro, and Saurina (2014), who study Spanish banks' risk-taking in response to euro-area policy rates. They consider the ECB's monetary policy to be exogenous to the credit risk that Spanish banks face. In our case, it is extremely unlikely that the FOMC decisions reflect concerns about the ex ante credit risk of loans being made by non-U.S. banks to borrowers in emerging market economies.

Thanks to Barth, Caprio, and Levine (2013), we can study the effects of broad and finely-defined bank supervision, regulation, and monitoring (SRM) characteristics that vary by time and country over the two decades, which include the period of unconventional monetary policy in the United States. In particular, we can establish which specific supervision or monitoring tools or types of regulation can mitigate a global risk-taking channel of U.S. monetary policy, as well as establish which tools have robust effects across monetary policy regimes. In a way, we can establish which SRM characteristics may dampen the supply of leveraged debt to the financial system broadly because of the nature of the market that we study (banks originate syndicated term loans to distribute them to shadow banks). Separately, we check whether another form of capital regulation—the implementation of Basel III—may have some mitigating effects on a risk-taking channel of U.S. monetary policy. We acknowledge that the implementation of Basel III is not a clean measure of a tightening of capital requirements because regulation that implements this accord typically tightens non-capital areas as well.

To set a baseline, we study the effects of lower U.S. policy rates on amounts of risky lending regardless SRM characteristics. We document a remarkable robustness of the economically-significant risk-taking channel of U.S. monetary policy across the samples and regression controls. It is operational in the samples that include or exclude U.S. borrowers, include a lot of U.S. banks or a lot of European banks, and span a decade or two. It is statistically significant in the regressions with the strictest specifications that include bank and borrower time fixed effects.

We study next the effects of broad supervisory powers on risk-taking and find that prompt corrective power, in particular, has an economically significant dampening effect on originations of risky loans in response to lower U.S. policy rates. (In fact, an increase in prompt corrective powers from the sample median level to the best practice level results in about 30 percent lower volumes of risky lending.) Figure 1 illustrates the gist of our findings for the global sample. It shows box plots of the distributions of amounts lent by banks to the riskiest borrowers across 4 U.S. policy rate and prompt corrective power environments (Low rates, low prompt corrective power; Low rates, high prompt corrective power; High rates, low prompt corrective power; and High rates, high prompt corrective power). The figure suggests that, in high rate environments, differences in amounts lent across low and high prompt corrective power environments are minimal. In contrast, in low rate environments, amounts lent in low prompt corrective power environments are significantly larger than those in high prompt corrective power environments (the median in dollar terms in the first box plot is nearly twice the same measure in the second box plot).[2] Note that the figure is for illustrative purposes and that it does not adequately reflect the complexity of the regression analysis.

As for other potential mitigants and their complementaries, we find that reporting transparency—specifically, financial statement transparency and accounting standards—but not activities restrictions and capital regulation, have robust dampening effects too. We also consider simultaneous effectiveness of SRM characteristics in mitigating a global risk-channel of U.S. monetary policy and show that prompt corrective power dominates or complements some other SRM characteristics.

Having identified prompt corrective power as a lead mitigant of on a global risk-taking channel of U.S. monetary policy, we study the effectiveness of specific, finely-defined prompt corrective powers. Barth, Caprio, and Levine (2013)'s index of broad corrective power has 7 finely-defined powers, 5 of which have statistically significant mitigating effects. They are power of automatic interventions at predetermined limits, cease and desists orders, suspension of dividends, suspension of bonuses, and suspension of management fees. Therefore, the effectiveness of prompt corrective power boils down to, on the one hand, having predetermined limits for automatic interventions and authority to force cessation of imprudent bank activities, and, on the other hand, to having authority to preserve bank capital by suspending payouts to equity holders and bank managers.

We are aware of the possibility that stricter supervision of banks may open the proverbial door for shadow banks to take over from banks originations of riskier loans, leaving overall originations of such loans unaffected (see, for example, Kim, Plosser, and Santos (2018)). Therefore, we check whether stricter bank supervision—specifically higher broad prompt corrective power—boosts loan originations by shadow banks. We do find evidence of the "revolving door of risk": Shadow banks

[2] Note that the figure does not adequately reflect the regression analysis. For example, in the figure, we do not control for bank or borrower characteristics.

take up a larger share in a loan syndicate when banks in that syndicate have supervisors with more prompt corrective power, particularly if the loan syndicate is risky. We also find evidence of a nonbank global risk-taking channel of monetary policy that is amplified when banks in a loan syndicate have supervisors with more prompt corrective power. We note though that economic significance of these findings is small because shadow banks' participation in loan originations is very limited.

We conclude that supervisory and reporting stringency may reduce financial risks from corporate leveraged debt by slowing down its build-up. Recall that banks engage in an originate-to-distribute model (they originate risky loans to sell fully or partially to shadow banks). Therefore, stricter SRM characteristics that slow down originations of risky loans can reduce the amounts of risky debt in the financial system more broadly. While, indeed, authorities may not have macroprudential tools to manage financial risks to the economy that emanate from corporate debt markets, other tools, such as stricter supervision, may be effective. In a way, we show that microprudential tools may have system-wide, macroprudential effects on risk-taking, but with small prudential "leakages" because of shadow bank participation in loan syndication. We conclude that local supervisory powers and reporting transparency may have global "macroprudential" effects.

The reminder of the paper is organized as follows. Section 2 places the paper in the literature. Section 3 describes key features of loan syndication and the global market for U.S dollar, Libor-indexed syndicated term loans; measures of ex ante credit risk of syndicated loan borrowers; measures of bank supervision, regulation, and monitoring; and, finally, the empirical methodology. Section 4 summarizes the estimation results. Section 5 runs a race between two characteristics at a time to identify the most robust mitigants of a global risk-taking channel of U.S. monetary policy. Section 6 studies specific finely-defined prompt corrective powers that mitigate risk taking. Section 7 examines the "revolving door of risk" hypothesis. Section 8 discusses caveats and robustness checks and the last section concludes with a few remarks on the implications of our findings for financial stability issues.

2 Place in the literature

We contribute to a few literature strands. The first two are more established: The literature on a risk-taking channel of monetary policy (Jimenez, Ongena, Peydro, and Saurina (2014), Ioannidou, Ongena, and Peydro (2015), Dell'Ariccia, Laeven, and Suarez (2017), Aramonte, Lee, and Stebunovs (2019), Lee, Liu, and Stebunovs (2019), and others) and the literature on the effectiveness of micro and macro-prudential tools and other mechanisms in mitigating the riskiness of banks or the riskiness of certain activities of banks (Delis and Staikouras (2011), Calem, Correa, and Lee (2019), and others). Out of the second strand, Delis and Staikouras (2011) is more closely related to our analysis. They find that effective supervision and market discipline requirements are important and complementary mechanisms in reducing bank fragility; and that, in contrast, capital requirements prove to be rather futile in controlling bank risk, even when supplemented with a higher volume of on-site audits and sanctions.

The third one is still very nascent: The literature on mitigants of a risk-taking channel of monetary policy, for example, Altavilla, Boucinha, Peydro, and Smets (2019) and, to a lesser extent, Maddaloni and Peydro (2011).

Altavilla, Boucinha, Peydro, and Smets (2019) analyze the role of banking supervision for banks' risk-taking behavior, and its interactions with monetary policy using over a dozen credit registries from the euro area. They exploit the one-time centralization of bank supervision for significant banks from a national level to a supranational level (the so-called single supervisory mechanism) over a period of the ECB's unconventional monetary policy. Essentially, it is a study of one, very specific event—a transition from (lax) national to (more stringent) supranational supervision in a period of unprecedented monetary policy in the euro area.[3] They find, among other things, that for banks operating in stressed countries only, centralized supervision reduces lending to riskier firms and that monetary policy easing increases bank risk-taking in stressed countries, with centralized supervision partly offsetting the effects.

In turn, Maddaloni and Peydro (2011) rely on euro-area bank lending surveys that began in the early 2000s to gauge risk-taking in household and corporate lending in response to the ECB's monetary policy. They find that banks ease general standards for household and corporate loans in response to lower policy rates and that banks ease lending standards due to their balance-sheet constraints less for mortgage but not corporate and consumer loans in countries with stricter (presumably overall) capital stringency (as defined by Barth, Caprio, and Levine (2013)). They note that their findings are consistent with theories suggesting that agency problems in the banking sector are crucial to explaining the risk-taking channel associated with low monetary policy rates (for example, Adrian and Shin (2010) and Dell'Ariccia, Laeven, and Marquez (2014)). While our analysis differs in many ways from that of Maddaloni and Peydro (2011)'s, we also find that capital regulation is not an effective mitigant of risk-taking in corporate lending.

In contrast to Altavilla, Boucinha, Peydro, and Smets (2019), we use global syndicated loan data which cover banks and borrowers from around the world. In addition, we study the effects of dozens finely-defined supervision, regulation, and monitoring characteristics that vary by time and country over two decades, which include the period of unconventional monetary policy in the United States. For example, we can establish which specific fine supervision or monitoring tools or types of regulation can mitigate a risk-taking channel of monetary policy, as well as establish which tools have robust effects across monetary policy regimes. In a way, we can establish which characteristics may slow down the supply of leveraged debt to the financial system more because of the nature of the market that we study. Recall that major banks originate syndicated loans to sell to shadow banks, such as mutual funds and collateralized loan obligations. Such findings may be of immediate relevance to policy makers contemplating financial risks emanating from corporate debt markets and ways to mitigate such risks.

[3] As Haselmann, Singla, and Vig (2019) show that national supervisors are systematically more lenient than the supranational supervisor.

3 Empirical methodology

In this section, we discuss our data and empirical methodology. First, we cover the specifics of syndicated term loan data. Second, we explain our choice of an ex ante credit risk measure. Third, we describe supervision, regulation, and monitoring characteristics that we draw from Barth, Caprio, and Levine (2013). Finally, we go over our regression specifications.

3.1 Syndicated term loan data

One of the advantages of studying the global syndicated loan market is its wide coverage of lenders of various nationalities that supply credit to borrowers of varying credit quality from around the world. A syndicated term loan is extended to a borrower by multiple lenders, that are not necessarily banks, that form a syndicate for that purpose, and it is administered by an agent, typically a bank. While there are two major types of syndicated loans—term loans and revolving lines of credit—we focus on the latter. Unlike revolving lines of credit, term loans are disbursed at origination, that is, they show up on bank balance sheets immediately, and, thus, they have significant immediate capital implications.[4] Term loans are senior in borrowers' liabilities and are typically of five-to-seven year maturity. So in some respects, term loans are similar to bonds.

We draw syndicated loan data from Refinitiv Loan Pricing Corporation DealScan. This data set contains detailed information on syndicated loans, including names, industries, locations of lenders and borrowers, and, for many loans but not all, lender shares in the syndicates at loan origination. We focus on syndication deals that are either closed or completed, with a distribution method being either syndication or club deal. We focus on loans that are denominated in U.S. dollars and are indexed to the U.S. dollar LIBOR.

We distinguish lenders by their type and syndication role. We rely on 4-digit SIC codes for primary activity given in the DealScan data to classify lenders and retain in the sample only those that are classified as banks, bank holding companies, and financial holding companies because they are subject to supervision, regulation, and monitoring that we study. The retained banks may play various roles from syndicate to syndicate, ranging from a participant to a lead agent. Participants typically have small shares in syndicates and may sell these shares quickly. In contrast, agents and arrangers play more significant roles in syndicates, have significant shares in those at origination, and typically retain significant shares over the lifetime of those. (In the global sample, the mean and median shares of agents and arrangers are twice as high as those of participants and in the non-U.S. sample three times as high.) Because agents and arrangers retain credit risk on their balance sheets over time, they are more likely affected by capital and other regulation.[5] And risk retention is particularly important for us. Banks originate syndicated loans with the intent to distribute

[4]Because borrowers can draw down revolving lines of credit at will, these lines have more complex pricing than term loans, see Berg, Saunders, and Steffen (2016). In addition, their originations and drawdowns are more endogenous to the credit and business cycles. For example, Ivashina and Scharfstein (2010) document a run by borrowers who drew down their lines, leading to a spike in corporate loans reported on U.S. bank balance sheets during the U.S. financial crisis of 2008.

[5]Our approach mimics that of Ivashina (2009) who defines mostly agents and arrangers to be lead banks in syndicates.

to shadow banks that either pre-commit to buy shares in the loans being originated or buy those shares shortly after the origination directly from the originators or in the secondary market. Lee, Liu, and Stebunovs (2019) find that the median of bank-owned shares in loans declines from about 90 percent to about 20 percent within a few weeks after loan origination.

From a perspective of a bank on a consolidated basis, some term loans are domestic loans (a bank head-quartered in country X lends to a borrower in the same country) and some term loans are cross-border loans (a bank head-quartered in country X lends to a borrower in another country). We retain both types of loans in the analysis, in part, to boost the sample size.

We also distinguish borrowers by their location and industry. We assign borrowers to one of 38 Fama-French's industry classifications (see Fama and French (1997)) based on borrower four-digit SIC codes for primary activity given in the DealScan data. We use borrower locations to construct a base sample (which includes borrowers from all countries) and a non-U.S. sample (which excludes borrowers from the United States) and to define various fixed effects.

The limited availability of lender shares in the syndicates at loan origination creates potential for biases. This is an issue that the literature has grappled with. For example, Ivashina (2009) does numerous checks to better understand the reporting biases and their evolution over the decades. Following Ivashina (2009), we control 1) for year fixed effects throughout the analysis to assure that the time effect in the reporting of the lead share does not affect the results and 2) for bank fixed effects to account for the stronger incentives of smaller banks to report the detailed information about their syndication activities.

3.2 Measure of ex ante credit risk

We have limited options for ex ante credit risk measures. Because our syndicated loan data set does not provide such measures, we cannot follow the approach of Dell'Ariccia, Laeven, and Suarez (2017) which relies on internal bank ratings of credit quality of new loans or the approach of Aramonte, Lee, and Stebunovs (2019) which uses banks' estimates of probabilities of loan default. Instead, we bring probabilities of default from another source, following Lee, Liu, and Stebunovs (2019). We focus on Moody's Analytics CreditEdge EDFs—forward-looking annualized probabilities of default at various horizons—as objective measures of borrower ex ante credit risk. These EDFs are based on the structural debt pricing model of Merton (1974) and historical global corporate default data. We use the most recent vintage of the EDF data that incorporates information from the GFC and post-GFC periods.[6] We then merge the EDF data and the Refinitiv LPC DealScan data by borrower names and other details using the matching algorithm in Cohen, Friedrichs, Gupta, Hayes, Lee, Marsh, Mislang, Shaton, and Sicilian (2018).[7] Of note, for a given loan-borrower EDF match, we retain an EDF for a horizon that approximates the maturity of the loan. We end up with a sample of thousands loans over the 1995-2014 period.

As Altunbas, Manganelli, and Marques-Ibanez (2017) note, the EDF methodology has various advantages. First, it is not based on ratings which might be biased indicators of corporate risk due

[6]See Nazeran and Dwyer (2015) for a detailed description of the modeling methodology.

[7]We thank Nathan Mislang for suggesting improvements for the matching algorithm.

to conflicts of interest. Second, unlike measures of default risks derived exclusively from accounting informationsuch as Z-scoresEDFs are not a backward-looking indicator of risk. Third, despite their simplifying assumptions, EDF estimations of default risk show strong robustness to model misspecifications (Jessen and Lando (2015)). Finally, over the recent financial crisis, EDFs have done relatively well as a predictor of firms risk on a cross-sectional perspective, compared to other measures of default risk. That is, the relative positions of firms ranked according to their EDF levels in the year before the crisis were good predictors of rank ordering of default risk during the crisis (Munves, Hamilton, and Gokbayrak (2009)). In turn, we add that EDFs are available for a much larger number of firms than credit ratings.

As Lee, Liu, and Stebunovs (2019) do, we admit that our measure of ex ante credit risk—probability of borrower default—is incomplete. We note that the literature in general suffers from the same issue. It is one of the two components of expected loss, with the other component being loss given default. Given data limitations, any estimates of losses given default will likely be highly inaccurate. But it is likely that losses given default have increased significantly over the sample period because of the proliferation of "covenant lite" loans, which have been in high demand from shadow banks.[8] Therefore, the omission of losses given default from analysis does not appear to be essential, because the proliferation of "covenant lite" loans works in our favor.

3.3 Measure of supervision, regulation, and monitoring

We draw information about supervision, regulation, and monitoring from Barth, Caprio, and Levine (2013)'s surveys that were released in 1999, 2003, 2007, and 2012 for 180 countries overall. These surveys have been widely used in the banking literature. The surveys include responses to hundreds of questions, including information on permissible bank activities, capital requirements, the powers of official supervisory agencies, loan provisioning, information disclosure requirements, and external governance mechanisms. Because the underlying surveys are large and complex, Barth, Caprio, and Levine (2013) construct summary indexes of SRM characteristics to facilitate cross-country comparisons and analyses of changes in banking policies over time.

We study the effects on a risk-taking channel of monetary policy of a subset of Barth, Caprio, and Levine (2013)'s indexes that capture the stringency of various aspects of supervision, capital regulation, private monitoring, and external governance are summarized, which we describe in table 1. We plot the averages of select indexes for the sample without U.S. borrowers (to show more time variation) in figure 3. We note that the surveys release years generally differ from the survey reference years. We focus on the references years when applying the surveyed characteristics to time intervals. We apply the characteristics from the 1999 survey for observations from 1995 through 2000, those from the 2003 survey for observations from 2001 through 2004, those from the 2007 survey for observations from 2005 through 2009, and those from the 2012 survey for observations from 2010 through 2014 (see figure 3).

[8] In general, covenant lite loans are riskier than other syndicated loans because they have few if any covenants to protect the lenders, such as restrictions on the borrowers regarding payment terms, income requirements, and asset disposals.

We cut the sample at 2014 because fast-changing SRM characteristics, in particular for European banks, which account for about 40 percent of sample observations, are not captured by the 2011 survey in Barth, Caprio, and Levine (2013). For instance, in response, to the GFC and the European sovereign and banking crises, the European Union adopted a number of initiatives in 2012 to create a safer banking system. These initiatives included a single rulebook for all financial actors in the 28 EU countries, a single supervisory mechanism (SSM), and a single resolution mechanism (SRM). After a period of preparatory work, the SSM, a part of the ECB, took over in late 2014 supervision of roughly 130 most significant banks in the euro area, a number of which shows up in our sample.[9] Less significant banks continue to be supervised by their national supervisors, but in close cooperation with the ECB. At any time the ECB can decide to directly supervise any one of these banks to ensure that high supervisory standards are applied consistently. Some of those banks show up in our sample too. In principle, we can justifiably cut the sample at 2013. However, as a robustness check, we cut the sample in Appendix at 2008 to show that the findings are not solely attributable to significant changes in SRM characteristics in response to the GFC and the European sovereign and banking crises (see figure 3) and to the federal funds rate being stuck at the zero lower bound since December 2008 with the Federal Reserves engaged in unconventional monetary policy (see figure 2).

We also check the effects of another form of capital regulation—Basel III Accord—on a global risk-taking channel of U.S. monetary policy. We draw the data on the timing on implementation of Basel III by country from Cerutti, Correa, Fiorentino, and Segalla (2017). As the literature does, we view the implementation of Basel III as a tightening of capital requirements. However, we add that there is more to the Accord than that. For example, the European Union's regulation that implements Basel III includes new definitions of capital, capital buffers, leverage ratio, but also of enhanced governance, enhanced supervision, a single rule book (regulation), counterparty credit risk, and liquidity risk. Therefore, one may argue that the implementation of Basel III is not a clean measure of a tightening of capital requirements.[10] We do not study the effects of Basel II because, per Cerutti, Correa, Fiorentino, and Segalla (2017), that accord was neutral in terms of capital requirements: Its introduction did not lead to a tightening nor a loosening of overall capital requirement regulations.[11]

3.4 Regression specifications

We posit that banks take U.S. interest rates and other factors as given and makes their risk-taking decisions in response to these factors. We associate short-term U.S. rates with the cost of

[9]The ECB has the authority to conduct supervisory reviews and on-site inspections and investigations; grant or withdraw banking licenses; assess banks' acquisition and disposal of qualifying holdings ensure compliance with EU prudential rules; set higher capital requirements to counter any financial risks.

[10]We also note an issue with the timing of the implementation: Regulators tend to implement Basel III in phases rather than outright.

[11]As stated by the Basel Committee, the objective of Basel II regarding the overall level of minimum capital requirements was "to broadly maintain the aggregate level of minimum capital requirements, while also providing incentives to adopt the more advanced risk-sensitive approaches of the revised framework" (Basel Committee on Banking Supervision 2006).

short-term U.S. dollar funding. We posit that lenders conduct risk management at the highest level of consolidation. Therefore, to the extent permitted by the data, we assign loans made by immediate lenders to their parent organizations, that is, ultimate lenders. For example, we assign a loan made by a bank to that bank's holding company. We first examine the sample to loans made by all banks to all borrowers. We then analyze the sample of loans made by all banks to non-U.S. borrowers.

We design our identification approach to deal with potential endogeneity of the riskiness of loans and U.S. monetary policy in multiple ways, even in the sample that includes U.S. borrowers. First, we study ex ante risk-taking by banks that reflects their risk attitude and tolerance at the time of loan originations. This focus on a margin that is under the control of banks (in contrast to the riskiness of their overall portfolios which reflect cyclical changes in loan quality), reduces greatly concerns about endogeneity of risk and monetary policy (Dell'Ariccia, Laeven, and Suarez (2017), Aramonte, Lee, and Stebunovs (2019), and Lee, Liu, and Stebunovs (2019)). Second, we exploit differences in characteristics of banks lending to the same borrowers, similar to Khwaja and Mian (2008)'s approach. Third, we identify the effects of interest through interaction terms (Kashyap and Stein (2000)) and, third, we saturate regression models with various time fixed effects to control for bank and borrower unobserved conditions.

However, to further dispel endogeneity concerns and to further strengthen the identification of the effects of U.S. monetary policy on risk-taking in the global syndicated loan market, we estimate regression models on a non-U.S. borrower sample where loans made by non-U.S. lenders to borrowers from emerging market economies represent a significant share of observations. In the former sample, we mimic the strategy of Jimenez, Ongena, Peydro, and Saurina (2014), who study Spanish banks' risk-taking in response to euro-area policy rates. They deem the ECB's monetary policy to be exogenous to the credit risk that the country's banks face. In our case, we believe that it is extremely unlikely that the FOMC decisions reflect concerns about the ex ante credit risk of loans being made by non-U.S. banks to borrowers in emerging market economies.

The analysis of the non-U.S. borrower sample complements and strengthens that of the global sample one for a couple of reasons. First, dropping loans made to U.S. borrowers reduces tremendously the weight in the sample of U.S. banks, which had operated in a strict and relatively stable SRM environment, and increases the weight of non-U.S. banks, which had experience numerous changes in their SRM environments. Therefore, we may identify more robust effects of SRM characteristics in the non-U.S. sample. Second, the findings for this non-U.S. borrower sample are of high interest in their own right: They may tell us about global risk-taking spillovers of U.S. monetary policy (as in Lee, Liu, and Stebunovs (2019)) and inform us about their potential mitigants.

We draw from Altavilla, Boucinha, Peydro, and Smets (2019) to define our regression model. In contrast to the typical approach in the literature on a risk-taking channel of monetary policy to put a loan rating or a probability of borrower default on the left in regression models, Altavilla, Boucinha, Peydro, and Smets (2019) use loan amounts and interact a loan risk characteristic with policy rates on the right. In turn, we put loan amounts on the left and on the right include various time fixed effects to control for unobserved factors, and identify the effects of interest through interactions terms (identification through heterogeneity of riskiness of borrowers and of SRM characteristics across countries where lenders are headquartered). We construct regressions at a loan level rather than a loan portfolio level to have borrower-level fixed effects.[12]

We estimate the following semi-log regression model:

$$
\begin{aligned}
log(Loan_{j,b,l,t}) = \gamma log(EDF_{j,b,t}) + \beta_S SRM_{l,t} + \theta_{SR} SRM_{l,t} \times R_t \\
+ \underbrace{\theta_{ER} log(EDF_{j,b,t}) \times R_t}_{risk-taking\ channel\ of\ MP} \\
+ \underbrace{\theta_{ES} log(EDF_{j,b,t}) \times SRM_{l,t}}_{general\ mitigation\ of\ risk-taking} \\
+ \underbrace{\theta_{ESR} log(EDF_{j,b,t}) \times SRM_{l,t} \times R_t}_{mitigation\ of\ risk-taking\ channel\ of\ MP} \\
+ \underbrace{\alpha_b + \alpha_l + \phi_{b,t} + \phi_{l,t}}_{fixed\ effects} + \varepsilon_{j,b,l,t}
\end{aligned}
\tag{1}
$$

where $Loan_{j,b,l,t}$ is bank l's loan j (a share in a syndicated loan) made to borrower b at time t.[13] $EDF_{j,b,t}$ is a Moody's Analytics CreditEdge EDF for borrower b at a horizon that matches the maturity of loan j. Note that we estimate a semi-log model with a log of EDF because of the pronounced skewness of the distribution of $Loan_{j,b,l,t}$s and $EDF_{j,b,t}$s. $SRM_{l,t}$ is a certain supervision, regulation, or monitoring characteristic of a country where bank l is head-quartered at time t. R_t is a U.S. policy rate, which is either the federal funds rate, the Wu and Xia (2016) shadow rate, or the 2-year U.S. Treasury rate. Our base rate is Wu and Xia (2016)'s because it shows the most time variation in the zero lower bound period.[14] α_l and α_b are bank and borrower fixed effects, respectively. $\phi_{b,t}$ and $\phi_{l,t}$ are time fixed effect, which vary across specifications. $\varepsilon_{j,b,l,t}$s are white noise errors which we cluster by time and bank to control for the dependence of observations across banks and within time. Regression models do not have controls for global push factors, local pull factors, and time-varying bank and borrower characteristics because we use various time fixed effects that make such controls redundant.[15]

We first estimate a regression model without SRM interaction terms for both for the global sample (which includes all borrowers) and the non-U.S. sample (which excludes U.S. borrowers) to set a baseline for a risk-taking channel of U.S. monetary policy. We then estimate regression models with SRM interaction terms included for both samples.

In output tables, the first four columns show the results for the global sample and the remaining four columns for the non-U.S. sample. Each column out of the each set of four shows the results for a regression model with a particular combination of fixed effects. Regression in all columns include

[12]Lee, Liu, and Stebunovs (2019) find that their risk-taking channel findings for loan-level regressions carry over to loan portfolio-level regressions.

[13]We rely on Correia (2016)'s estimator for linear models with multi-way fixed effects and error clustering.

[14]While the shadow rate is widely used in the literature, its interpretation in banking applications is not clear: Banks neither explicitly pay the shadow rate on their liabilities nor receive it from their assets. Thus, in the robustness checks, we rely on the other two choices.

[15]For example, global push factors include risk appetite, economic uncertainty, and the U.S. dollar exchange rate and local pull factors include economic growth and interest rates in borrower countries.

bank fixed effects to control for latent constant characteristics of each bank. These effects likely do a fine job in regressions that cover shorter periods of calm, similar years but not in regressions that cover longer, eventful periods. Regressions in all columns also include borrower fixed effects to control for latent constant characteristics of each borrower. Some borrowers may borrow only one syndicated loan over a sample period. However, their loans will appear in the dataset multiple times because multiple banks in a syndicate lend to them. Therefore, the fixed effects for these borrowers essentially control for their characteristics and loan demand around loan originations. Then, for a given borrower, variation in SRM characteristics of lenders explains the remaining variation. In columns 1 and 5, we include bank-country and borrower-country time fixed effects. In columns 2 and 6, we include individual bank time fixed effects and borrower-country time fixed effects. In columns 3 and 7, we retain individual bank time fixed effects but replace borrower-country time fixed effects with borrower-industry time fixed effects. We assign borrowers to one of 38 Fama-French's industry classifications based on borrower four-digit SIC codes. Finally, in our most stringent specification in columns 4 and 8, we retain individual bank time fixed effects but replace borrower-industry time fixed effects with individual borrower time fixed effects. Going from the base specification to the most stringent one, some regressors drop out and the number of observations shrinks by about a half.

To connect the hypotheses with the literature, we note that the hypotheses about general mitigation of risk-taking follow from the strand on the effectiveness of micro tools and other mechanisms in reducing build-ups in ex ante credit risk. For example, Delis and Staikouras (2011) find that effective supervision and market discipline requirements are important and complementary mechanisms in reducing bank fragility; and that, in contrast, capital requirements prove to be rather futile in controlling bank risk, even when supplemented with a higher volume of on-site audits and sanctions. While some papers are not exactly on the effectiveness of activities restrictions per se, they still hint at activities restrictions that may stem general risk-taking. For example, DeYoung and Torna (2013) test whether reliance on income from nontraditional banking activities contributed to the failures of hundreds of U.S. commercial banks during the financial crisis. Their estimates indicate that the probability of distressed bank failure declined with pure fee-based nontraditional activities such as securities brokerage and insurance sales, but increased with asset-based nontraditional activities such as venture capital, investment banking, and asset securitization. They also find that banks that engaged in risky nontraditional activities also tended to take risk in their traditional lines of business. In turn, Beltratti and Stulz (2012) evaluate the importance of factors that have been put forth as having contributed to the poor (stock returns) performance of banks during the GFC. Among other things, they find that differences in banking regulations across countries are generally uncorrelated with the performance of banks during the crisis, except that large banks from countries with more restrictions on bank activities performed better and decreased lending less. As for the recent euro-area experience, Haselmann, Singla, and Vig (2019) show that banks under the single supervisory mechanism report higher risk weights, higher probability of default, and lower collateral to loan ratios for exposures to the same firms than banks under lenient national supervision. This differential regulatory treatment results in higher capital charges for banks under the single supervisory mechanism, which activities ultimately curtails their holdings of risky assets.

The literature on the effectiveness of SRM characteristics in mitigating a (global) risk-taking channel of monetary policy appears to be more limited and but does offer a few clues. Altavilla, Boucinha, Peydro, and Smets (2019) finds that stricter official supervision, vaguely defined, may help under certain economic conditions. Lee, Liu, and Stebunovs (2019) find that risk-taking of U.S. banks to changes in U.S. interest rates is less sensitive than that of non-U.S. banks and that of nonbanks. They speculate that one of the reasons is that U.S. banks are subject to stricter supervision and regulation than banks in other countries or nonbanks in general. And speaking of stricter regulation, it is possible that stricter capital regulation amplifies rather than mitigates a risk-taking channel of monetary policy. For example, consider that Dell'Ariccia, Laeven, and Suarez (2017) and Lee, Liu, and Stebunovs (2019) find that risk-taking in response to lower U.S. interest rates was more prominent for banks with relatively high capital. However, capital regulation may have no effect at all. For example, Maddaloni and Peydro (2011)'s survey-based work shows that capital regulation is not an effective mitigant of risk-taking in corporate lending.

Across the specifications, we identify the effects of interest through interactions terms and focus on the same three regression coefficients. The first coefficient—that on the interaction of log(EDF) and a U.S. policy rate—captures a risk-taking channel of U.S. monetary policy. Based on the finding in the literature, we hypothesize a negative coefficient: Lenders lend more to more risky borrowers in response to a policy easing. To set a baseline for this coefficient, we estimate a version of model 1 which omits supervision, regulation, or monitoring interaction terms. The hypothesized signs of the remaining coefficients of interest appear in table 4. The second coefficient—that on the interaction of log(EDF) and a regulation, supervision, or monitoring characteristic—informs about general mitigation of risk through stricter supervision, regulation, or monitoring. We generally hypothesize a negative coefficient as well: Lenders that face more scrutiny or stricter regulation lend in general less to more risky borrowers. However, as we noted earlier, certain activities restrictions may amplify rather than mitigate risk-taking. Finally, the third coefficient— that on the triple interaction of log(EDF), a supervision, regulation, or monitoring characteristic, and a U.S. policy rate—captures mitigation of a risk-taking channel of U.S. monetary policy through supervision, regulation, or monitoring. We generally hypothesize a positive coefficient: Lenders that face more scrutiny or stricter regulation lend less to more risky borrowers in response to a policy easing. However, as we brought up earlier, stricter capital regulation may amplify rather than mitigate a risk-taking channel of monetary policy.

To gauge the overall effects of U.S. policy rates and supervision, regulation, or monitoring on risk-taking, we construct two measures. The first measure is a marginal effect of one standard deviation change in a U.S. policy rate, $stand.dev._R$, conditional on certain thresholds of borrower credit risk, $log(\overline{EDF})$, and of supervision, regulation, or monitoring, $\overline{SRM}$. Note that the marginal effect also depends on a reference point of the explained variable, $\overline{Loan}$, because model (1) is a semi-log model for a U.S. policy rate. The formula for the marginal effect (in basis points) then is:

$$\begin{aligned} \Delta Loan = 100 \times \overline{Loan} \\ \times(\theta_{ER} + \theta_{ESR} \times \overline{SRM}) \times log(\overline{EDF}) \\ \times stand.dev._R. \end{aligned} \tag{2}$$

In light of the hypotheses and the data characteristics, the effects of a policy rate change may be very different across thresholds. For safer borrowers or/and for more scrutinized banks, the effect may be small, and, for risky borrowers or/and less scrutinized banks, it may be substantial. The second measure is a change in the first measure conditional on a change in supervision, regulation, or monitoring:

$$\Delta(\Delta Loan) = \Delta Loan \mid \overline{SRM}_0 - \Delta Loan \mid \overline{SRM}_1. \tag{3}$$

This latter measure helps to evaluate the potential economic significance of an increase in bank scrutiny ($\overline{SRM}_1 > \overline{SRM}_0$).

We consider simultaneous effectiveness of select characteristics in mitigating a global risk-channel of U.S. monetary policy. In such "horse race" regressions, we include two characteristics at a time to identify the characteristics that have most robust or complementary effects. Because of not all SRM characteristics are available for all countries for all years and because of space constraints, we examine only the characteristics that have the most robust effects across the samples in individual characteristic regressions.

4 Estimation results

In this section, we present the estimation results. Table 2 lists the countries of banks and borrowers that appear in the global and non-U.S. borrower samples. Loans made by U.S. banks and loans made to U.S. borrowers represent significant shares of the global sample. Loans made by Asian banks and loans made to borrowers in emerging market economies represent significant shares of the non-U.S. borrower sample. Table 3 provides descriptive statistics for the samples that include and excluded U.S borrowers.

In all regressions, the coefficients that capture a risk-taking channel of U.S. monetary policy are negative and statistically and economically significant ($\theta_{ER} < 0$ and statistically significant at a 5 percent or lower level; banks do lend more to more risky borrowers in response to a policy easing). Thus, we confirm a well-established result (for example, Dell'Ariccia, Laeven, and Suarez (2017), Aramonte, Lee, and Stebunovs (2019), and Lee, Liu, and Stebunovs (2019)), but in a very different regression setting. As we mentioned earlier, the literature typically puts credit risk measures on the left, whereas we put loan amounts (similar to Altavilla, Boucinha, Peydro, and Smets (2019)).

Across the regressions, the coefficients that capture general mitigation of risk-taking are negative and generally statistically and economically significant ($\theta_{ES} < 0$; banks that face more scrutiny do lend in general less to more risky borrowers). Again, we get similar results to those in the literature on general mitigation of risk through stricter supervision and monitoring (for example, Delis and Staikouras (2011) who use a different regression setup).

We pay particular attention to the coefficients that capture mitigation of a risk-taking channel of U.S. monetary policy ($\theta_{SRM} > 0$; banks that face more scrutiny do lend less to more risky borrowers in response to a policy easing). For those, we provide a summary of the estimation results in table 4, which highlights the signs of the coefficients that are statistically significant in at least 2 out of 4 specifications. The coefficients on characteristics in bold are also statistically significant in regressions estimated over the 1995-2008 period. Out of 18 SRM characteristics that we consider, only 10 have statistically significant effects on a risk-taking channel of monetary policy over the 1995-2014 period. All but one of the 10 characteristics have mitigating effects on the channel. The standout is supervisory forbearance power which amplifies, rather than mitigates, a risk-taking channel of U.S. monetary policy. Only 4 of the 10 have statistically significant effects in the regressions estimated over the shorter sample from 1995 to 2008. They are prompt corrective power, declaring insolvency power, financial statement transparency, and accounting practices. The implementation of Basel III had some mitigating effect of a global risk-taking channel of U.S. monetary policy.

4.1 Baseline: No SRM characteristics

To set a baseline, we study the effects of lower U.S. policy rates on amounts of risky lending regardless SRM characteristics. The estimation results are in table 5 and the marginal effects in panel A of table 7. We document a remarkable robustness of the economically-significant risk-taking channel of U.S. monetary policy across the samples and regression controls. It is operational in the samples that include or exclude U.S. borrowers, include a lot of U.S. banks or a lot of European banks, and span a decade or two. It is statistically significant in the regressions with the strictest specifications that include bank and borrower time fixed effects.

4.2 Official supervision

We show in tables 6, 8, and 9 the results for 4 supervision power characteristics that have statistically significant effects on a risk-taking channel of monetary policy. Out of these 4 characteristics, prompt corrective power stands out: It has strong mitigating effects in both longer and shorter samples. We show marginal effects of a lower federal funds rate on originations of ex ante risky loans conditional on a given level of supervisory power and changes in marginal effects conditional on changes in a level of supervisory power in table 7. (The table shows that raising the stringency of prompt corrective power from the sample median to the level of "best practice" of 6 substantially reduces risk-taking.)

In light of the hypotheses and the data characteristics, the effects of a policy rate change may be very different across thresholds. For safer borrowers or/and for more scrutinized banks, the effect may be small, and, for risky borrowers or/and less scrutinized banks, it may be substantial. The second measure is a change in the first measure conditional on a change in supervision, regulation, or monitoring: equation 3. We base the calculations on the estimation results in column (8) of table 6. We assume a one standard deviation decrease in the federal funds rate and an increase in the prompt corrective power characteristic from its median to the 75th percentile. The change in the marginal effect is about 20 percent of the marginal effect, no matter the EDF threshold.

Prompt corrective power is likely a significant mitingant because it allows supervisors identify issues more easily and respond to these issues quickly. To illustrate this point, we reproduce some of the questions that Barth, Caprio, and Levine (2013) use to construct their index for this particular characteristic for 2011: Does the supervisory agency operate an early intervention framework that forces automatic action when certain regulatory triggers/thresholds are breached? Does the supervisory authority have the following enforcement powers: Cease and desist-type orders for imprudent bank practices; require a bank to meet supervisory capital and liquidity requirements that are stricter than the legal or regulatory minimum; require bank to enhance governance, internal controls and risk management systems; require bank to apply specific provisioning and/or write-off policies; restrict or place conditions on the types of business conducted by bank; withdraw the bank's license; require banks to reduce/restructure their operations and adjust their risk profile; suspend or remove bank directors; suspend or remove managers; require commitment/action from controlling shareholder(s) to support the bank with new equity; require banks to constitute provisions to cover actual or potential losses; require banks to reduce or suspend dividends to shareholders; require banks to reduce or suspend bonuses and other remuneration to bank directors and managers. We list Barth, Caprio, and Levine (2013)s' all finely-defined prompt corrective powers in table 15 and explore the effectiveness of each them in a later section.

Not all supervision powers have mitigating effects on a risk-taking channel of monetary policy. We find that supervisory forbearance discretion amplifies, rather than mitigates, a risk-taking channel (see table 9). This finding is period specific though.

4.3 Activities restrictions and capital regulation

We show in the appendix the results for activities restrictions characteristics—real estate activities and securities activities—that have statistically significant effects on a risk-taking channel of monetary policy over the longer sample period (tables A3 to A4). The results for the two activities restrictions are sample period specific: They do hold for the longer period but not for the pre-crisis period which suggests that the tightening of such activities in response to the financial crises amid the tightening of more general banking regulation may explain the findings. In short, it appears that while activities restrictions may be helpful, there are some reasons to discount their effectiveness. Insurance activities restrictions appear to have statistically significant effect in either the pre-crisis or longer samples.

Capital regulation is not than of those characteristics with statistically significant effects (see table A5 in the appendix). On the one hand, it may be that banks originate risky loans and sell them quickly before reporting dates (quarter- and year-ends) to window dress, therefore, capital constraints may not be binding and capital regulation may have little effect on risk-taking. In a way, this finding may point at preponderance of capital regulation arbitrage. On the other hand, some papers on a risk-taking channel of U.S. monetary policy do find that the low levels of capitalization weigh on risk-taking. For example, Dell'Ariccia, Laeven, and Suarez (2017) find that ex ante risk-taking by U.S. banks (measured by the risk rating of new loans) in originations of small, domestic, non-syndicated business loans is negatively associated with increases in short-term U.S. interest rates was less pronounced for banks with relatively low capital. In a more closely related study, Lee, Liu, and Stebunovs (2019) find that risk-taking behavior was less prominent for banks with relatively low capital risk-taking in response to longer-term U.S. interest rates in the global syndicated term loan market. They suggest that, given the overall environment, including tightened supervisory scrutiny, banks with relative low capital were more likely in the post-crisis period to preserve their capital rather than gamble for resurrection. We can think of a reason behind the differences in the findings: Stricter capital regulation does not necessarily translate into higher bank capital ratios. Indeed, we cannot document a positive correlation between Barth, Caprio, and Levine (2013)'s capital regulation characteristics and bank system-level capital ratios across countries (see figure 4). Barth, Caprio, and Levine (2013)'s questions on capital regulation are about characteristics of capital regulation regimes rather than about the levels of regulatory capital ratio minimums. For example, the 2011 survey questions ask which regulatory capital adequacy regimes was applicable (Basel I, Basel II, leverage ratio) by bank type; which risks were covered by the regulatory minimum capital requirements (Credit risk, Operational risk, Market risk); which items were deductible from regulatory capital (Goodwill, Deferred tax assets, Intangibles, Unrealized losses in fair valued exposures); and so on.

Switching to another form of capital regulation, the implementation of Basel III may have some mitigating effects on a risk-taking channel of U.S. monetary policy. As table A6 shows, in the sample that includes U.S. borrowers, the implementation mitigates the channel in 2 out of 4 regressions (the ones with the strongest controls for unobserved time fixed effects on both bank and borrower sides). One sample country has begun implementing Basel III in 2012, with the others following in 2013 (for example, Japan and Taiwan) and 2014 (the United States). Out of over 8000 observations in column 1, nearly 1300 are in Basel III regimes across the countries. Out of these 1300, U.S. banks account for nearly 300, Taiwanese banks for nearly 280, and Japanese banks for nearly 200. Therefore, one may attribute the mitigating effect to observations for U.S. banks, which have a large weight in the sample and which may engage less in risk-taking for other reasons, for example, because of more stringent supervision. To address this possibility, we run regressions with Basel III and prompt corrective power characteristics included and show that Basel III still has some mitigating effect, see table A10 in the appendix.[16] We note that there is more to Basel II than stricter capital requirements. Therefore, one may argue that the implementation of Basel III is not a clean measure of a tightening of capital requirements.

4.4 Private monitoring and external governance

We show in tables 10 to 11 the results for 2 private monitoring and external governance characteristics that have robust statistically significant effects on a risk-taking channel of monetary policy. These metrics—financial statement transparency and accounting practices—have statistically significant effects on risk-taking in both periods. The findings suggest that some forms of private monitoring—transparency of reporting, specifically—complement official supervision in mitigating a risk-taking channel of monetary policy. We discount the importance of bank accounting (the characteristic which, among other things, specifies showing unpaid interest in income statements) because it has no statistically significant effect in the short sample. (We less concerned about

[16] We also check the robustness of the Basel III finding against declaring insolvency power, see the appendix.

this characteristic having a statistically significant effect only in the sample without U.S. borrowers. That sample is dominated by U.S. banks which had been subject to such bank accounting consistently throughout the sample period.)

5 Mitigants robustness and complementarity

We now consider simultaneous effectiveness of select characteristics in mitigating a global risk-channel of U.S. monetary policy. In the following “horse race” regressions, we include two characteristics at a time to identify the characteristics that have most robust or complementary effects. Because not all SRM characteristics are available for all countries for all years and because of space constraints, we examine only the characteristics that have the most robust effects across the samples in individual characteristic regressions, see table 4. These characteristics are two supervisory powers—prompt corrective power and declaring insolvency power—and two transparency characteristics—financial statement transparency and accounting practices.

We pay particular attention to the coefficients that capture mitigation of a risk-taking channel of U.S. monetary policy ($\theta_{SRM} > 0$; banks that face more scrutiny do lend less to more risky borrowers in response to a policy easing). We show the results in tables 12 to 14 for the horse races regressions between prompt corrective power and other mitigants over the longer, 1995-2014 period and on those for the regressions over the shorter, 1995-2008 period in tables A23 to A27 in the appendix. The summary suggests that prompt corrective power dominates insolvency power (and complements some of the other mitigating characteristics).

This finding—that prompt corrective power, meaning early actions, is more effective than insolvency declaration power, meaning late actions—is not surprising. In a way, the former are going concern actions, meaning a given bank is viable but has been engaged in imprudent activities which supervisory action can address quickly, whereas the former are gone concern actions, meaning a given bank has done imprudent things in the past and has suffered so much that it is beyond repair and has to be resolved.

Rezende and Wu (2013) offer some clues on the effectiveness of prompt corrective power. They note that earlier research has found little evidence that banking supervision improves bank performance, possibly because supervision is endogenous to performance and then, for the United States, they estimate causal effects of supervision on performance using discontinuities in the minimum frequency of examinations imposed by regulation. They find that more frequent examinations increase profits and decrease loan losses and delinquencies. This is consistent with the hypothesis that regulators limit the risks that banks are exposed to and, consequently, limit their losses on risky assets.

Separately, we note that the results suggest that insolvency power and financial statement transparency complement prompt corrective power in mitigating a global risk-taking channel of U.S. monetary policy (the coefficients on the interaction terms of interest are simultaneously statistically significant for prompt corrective power and one of the other SRM characteristic). Based only on the global sample results, Basel III may have some complementarity with prompt corrective power and insolvency power (see tables A10 and A11).

In principle, official supervision and private monitoring and external governance provide alternative devices for controlling banks and government oversight can displace private efforts to evaluate and control banks (Flannery (1998)). Our findings suggest a combination of government and private supervision that operates concurrently. Flannery (1998) observes the evidence that supports the proposition that market investors and analysts could reasonably provide a greater proportion of corporate governance services for large, traded U.S. financial firms. While higher reporting transparency improves private investors' abilities to assess the financial condition of banks, it still cannot substitute but can complement effective prompt corrective power.

6 Finely-defined prompt corrective powers

We study specific finely-defined prompt corrective powers that mitigate risk taking. Barth, Caprio, and Levine (2013)'s index of prompt corrective power has 7 components that come out of detailed survey questions and that have, in a way, unequal weights. We summarize these components in table 15. If the first component is equal to zero then the overall index of prompt corrective power is zero, no matter the remaining components.

We reestimate regression models (equation 1) with SRM replaced with one component of prompt corrective power at a time. We show the detailed results for components that have statistically significant mitigating effects in tables 16 to 20. Out of the 7 components, only 5 have statistically significant mitigating effects. They are early automatic intervention authority, cease and desist order, suspension of dividends, suspension of bonuses, and suspension of management fees. The first 3 out of the 5 have such effects no matter the sample of borrowers. In short, the effectiveness of prompt corrective power boils down to, on the one hand, having early automatic interventions and authority to force cessation of imprudent bank activities, and, on the other hand, to having authority to preserve bank capital by suspending payouts to equity holders and bank managers. (We show the results for regressions estimated over the 1995-2008 period in Appendix .)

Our findings about the timing of formal enforcement actions echoes those of the banking supervision literature. For example, Delis, Staikouras, and Tsoumas (2017) find, albeit with some limitations, that the longer the actions are deferred relative to the deterioration of a bank's financial condition, the more limited their effect on the risk-based capital ratio. That is, Delis, Staikouras, and Tsoumas (2017)'s results are consistent with the idea that an action deferral enables a bank to take more risks which ultimately reduce its financial soundness. As for our findings about the effectiveness of payout suspensions, the literature—for example, Pugachev (2019)—finds that, in the United States, enforcement actions that restrict payouts, but not other enforcement actions, elicit negative abnormal returns in their aftermath. Moreover, Pugachev (2019)'s results on the cross-section of abnormal returns suggest that risk-shifting from equity holders, in particular, inside owners, towards other claimants, rather than agency cost-reduction, drives payouts and supports the value of bank equity.

7 "Revolving door of risk" and a nonbank risk-taking channel of monetary policy

We are aware of the possibility that stricter supervision of banks may open the proverbial door for shadow banks to take over from banks originations of riskier loans, leaving overall originations of such loans unaffected. For example, Kim, Plosser, and Santos (2018) find that the 2013-14 U.S. interagency guidance on leveraged lending (a novel but temporary U.S. macroprudential tool) triggered a migration of leveraged lending from large, closely supervised banks to nonbanks. They question the effectiveness of macroprudential regulations in reducing the risk that risky loans pose for the stability of the financial system. The statistics in Kim, Plosser, and Santos (2018), however, suggest that the potential leakages are modest. While banks account for most of the leveraged lending, nonbank lenders have been increasing their presence in the U.S. market. The number of leveraged loans they extend prior to the guidance is only 7.4 percent of the number extended by banks. In the period after the clarification to the guidance, that percentage rises to 10.9 percent. The increase is larger in terms of the volume of loans as it increases from 4.3 percent to 8.3 percent.

While shadow banks' participation in loan originations in our data is similarly limited, we, nevertheless, check whether stricter bank supervision boosts loan originations by shadow banks. Specifically, we modify model 1 to identify the effects of stricter supervision of agent and arranger banks on shadow bank participation in originations of risky loans. Because the same shadow banks appear in the data only sporadically, we cannot have elaborate controls for such lenders. Consequently, we aggregate the data and, for a given syndicate, focus on an overall shares of shadow banks rather than on individual shares of shadow banks.

We estimate the following linear regression models:

$$
\begin{aligned}
NBS_{j,b,t} = \gamma log(EDF_{j,b,t}) + \beta_S \overline{SRM}_{j,t} + \eta_{SR}\overline{SRM}_{j,t} \times R_t \\
+ \underbrace{\eta_{ER} log(EDF_{j,b,t}) \times R_t}_{risk-taking\ channel\ of\ MP} \\
+ \underbrace{\eta_{ES} log(EDF_{j,b,t}) \times \overline{SRM}_{j,t}}_{general\ amplification\ of\ risk-taking} \\
+ \underbrace{\eta_{ESR} log(EDF_{j,b,t}) \times \overline{SRM}_{j,t} \times R_t}_{amplification\ of\ risk-taking\ channel\ of\ MP} \\
+ \underbrace{\alpha_b + \phi_{b,t}}_{fixed\ effects} + \varepsilon_{j,b,t}
\end{aligned}
\tag{4}
$$

where $NBS_{j,b,t}$ is an overall share (in percent) of shadow banks in syndicate j made to borrower b at time t. Note that in contrast to model 1, we estimate linear models because the right hand side variable is often zero. In addition, we switch from loan share defined in U.S. dollars to those defined in percent because we do not include borrower fixed effects, which in part control for loan sizes, to boost the degrees of freedom. As earlier, $EDF_{j,b,t}$ is an EDF at a horizon that matches the maturity of syndicate j. $\overline{SRM}_{j,t}$ is weighted average of a certain supervision, regulation, or monitoring characteristic of a country where agent and arranger banks of syndicate j are headquartered at time t. As earlier, R_t is a U.S. policy rate, which is either the federal funds rate, the Wu-Xia shadow rate, or the 2-year U.S. Treasury rate. α_b is a borrower country and industry fixed effect rather than individual borrower fixed effect.[17] $\phi_{b,t}$ is a time fixed effect, which varies across specifications (simple time fixed effect, borrower-country time fixed effect, or borrower-industry time fixed effect). These time fixed effects wash out R_t. $\varepsilon_{j,b,t}$s are white noise errors which we cluster by time. We estimate these models on the same sample as we use in the earlier regressions. We rely on Refinitiv Loan Pricing Corporation (LPC) DealScan's classification of lenders to identify shadow banks in loan syndicates.

Across the specifications, we identify the effects of interest mostly through interaction terms and focus on the same regression coefficients: β_S and most of the ηs. Based on the finding in the literature, we hypothesize positive coefficients β_S and η_{ES}: Shadow banks take up a larger share in a syndicate when banks in that syndicate face more scrutiny, particularly if the syndicate is risky ("revolving door of risk"). Consequently, we label the interaction term $\eta_{ES} log(EDF_{j,b,t}) \times \overline{SRM}_{j,t}$ as "general amplification of risk-taking". Next, we hypothesize a negative coefficient η_{ER}: Shadow banks take up larger shares in syndicates made to more risky borrowers in response to a policy easing.[18] We label the interaction term $\eta_{ER} log(EDF_{j,b,t}) \times R_t$ "risk-taking channel of monetary policy". Finally, we hypothesize a negative coefficient η_{ESR}: Shadows banks take up a larger share in a syndicate made to more risky borrowers in response to a policy easing when banks in that syndicate face more scrutiny. We label the interaction term $\eta_{ESR} log(EDF_{j,b,t}) \times \overline{SRM}_{j,t} \times R_t$ "amplification of risk-taking channel of MP".

Before turning to the estimation results, we reiterate that the descriptive statistics suggest that shadow banks tend to take small shares in syndicates at origination (bottom panel in 3), as in Kim, Plosser, and Santos (2018)'s sample. Shadow banks participate in origination of only a small portion of loans (the median of loan shares of nonbanks is 0 percent). Shadow banks' participation in loan originations is a new phenomenon, so most of loans with non-zero nonbank shares were in the later sample years.

We show the estimation results in table 21 for prompt corrective power. We do find evidence of the "revolving door of risk": Shadow banks take up a larger share in a syndicate when banks in that loan syndicate face more scrutiny, particularly if the loan syndicate is risky. We also find evidence of a nonbank risk-taking channel of monetary policy that is amplified when banks face more scrutiny. We note yet again that economic significance of these findings is small because shadow banks' participation in loan originations is very limited.

[17] Inclusion of individual borrower fixed effects would have more than halved the number of observations.
[18] The coefficient η_{SR} may be negative as well.

8 Checks and caveats

We check whether the findings are robust to alternative U.S. policy rates. First, we reestimate regression models 1 with U.S. monetary policy captured by the 2-year U.S. Treasury yield, which reflects not only the spot federal funds rate of U.S. monetary policy but also a market-expected path of the federal funds rates (that is, funding costs) over the next two years. In some sense, because financial intermediaries in general and banks in particular act upon the expectations of U.S. monetary policy, the 2-year U.S. Treasury yield is a more comprehensive and relevant measure.[19] The limitation of the yield is greater than that of the federal funds rate but still limited time variation in the zero lower bound period (see figure 2). Second, we reestimate the regressions with U.S. monetary policy captured by the federal funds, including the zero lower bound period. Third, we also address any lingering concerns about the endogeneity of the federal funds rate and ex ante credit risk: We reestimate the regression models with a first lag of the federal funds rate. The key results (on prompt corrective power and other characteristics) generally hold up.

We also check the robustness of the estimation results to the assignment of Barth, Caprio, and Levine (2013)'s surveys to certain time intervals: We apply that those characteristics for an interval beginning the reference year up to the year of the next survey, effectively as in Karolyi and Taboada (2015). The key results hold up. Some of the estimation results are shown in the appendix (regressions with the federal funds rate for the sample that end before the crisis, that is, in 2008), the others are available on request.

As for caveats, our findings may reflect two latent reasons for the effectiveness of bank supervision. First, as we discussed earlier, agents and arrangers retain larger shares in syndicated loans post origination. Therefore, their participation in risky lending is more evident to bank supervisors. Second, agents and arrangers tend to be larger banks which likely implies that supervisors pay more attention to them. In the analysis, we do not differentiate the reasons, in part, because we have data neither on the sample loans post origination (for risk retention analysis) nor on the extent of supervisory attention (such as prompt corrective action notices, on-sight inspections, and so on). That said, we considered doing analysis by bank size (where a bank's size relative to other banks in a given country acts as a proxy for the extent of supervisory attention) but did not because of concerns that in a panel of globally active banks of various size, size alone may be an inadequate criterion to determine the extent of supervisory attention.

9 Conclusions

Figuring out mitigants to risk-taking in response to lower policy rates in corporate loan markets is particularly relevant because macroprudential tools at the disposal of central banks and other regulators to manage financial risks are not designed to deal with threats emanating from such markets. We study potential mitigants of ex ante risk-taking by banks in response to lower policy rates. In particular, we focus on the mitigating effects of official supervision; activities restrictions

[19] Aramonte, Lee, and Stebunovs (2019) find that both banks and shadow banks take on more ex ante credit risk in response to both lower spot and forward interest rates.

and capital regulation; and private monitoring and external governance on originations of risky term loans by banks in the global market for syndicated U.S. dollar loans. We find that supervisory powers—in particular, certain prompt corrective powers—have an economically significant dampening effect on originations of risky loans in response to lower U.S. policy rates. In a way, we show that microprudential tools have macroprudential effects. We also find small prudential "leakages" because of shadow bank participation in loan originations. Reporting transparency, but not activities restrictions and capital regulation, have robust dampening effects too. We conclude that supervisory stringency and reporting transparency may reduce financial stability risks from corporate leveraged debt by slowing down its build-up. We note that the results suggest that insolvency power and financial statement transparency complement prompt corrective power in mitigating a global risk-taking channel of U.S. monetary policy. They are early automatic intervention authority, cease and desist order, suspension of dividends, suspension of bonuses, and suspension of management fees. The first 3 out of the 5 have such effects no matter the sample of borrowers. In short, the effectiveness of prompt corrective power boils down to, on the one hand, having early automatic interventions and authority to force cessation of imprudent bank activities, and, on the other hand, to having authority to preserve bank capital by suspending payouts to equity holders and bank managers.

As in Lee, Liu, and Stebunovs (2019), the existence of a global risk-taking channel and global risk-taking spillovers of the Federal Reserve's monetary policy highlights two financial stability challenges. First, other central banks may find it harder to have an effect on risk-taking in their countries in the presence of large, globally active banks whose risk-taking decisions are, in part, driven by U.S. monetary policy. Second, the presence of such banks implies that build-ups in ex ante credit risk are global in nature. These banks originate riskier loans in the global primary market, partly sell them off to shadow banks in the global secondary market, and hedge potential loan defaults (exposing their hedge counterparties to such defaults) in the global CDS market. Hence, additional risk-taking by globally active banks could strain the global financial system. To this end, central banks may have to rely on coordination of multiple policy tools to ensure both economic and financial stability. We find that microprudential tools may work well.

While we focus on mitigation of risk-taking in normal times, supervisors may be choose to do the opposite in a pandemic—to stimulate risky lending by easing the stringency in a pandemic. In fact, the literature appears to suggests that supervisory stringency or rather the intensity of supervision may be state-dependent.

References

ADRIAN, T., AND H. S. SHIN (2010): "Financial Intermediaries and Monetary Economics," in *Handbook of Monetary Economics*, ed. by B. M. Friedman, and M. Woodford, vol. 3 of *Handbook of Monetary Economics*, chap. 12, pp. 601–650. Elsevier.

ALTAVILLA, C., M. BOUCINHA, J.-L. PEYDRO, AND F. SMETS (2019): "Banking Supervision, Monetary Policy and Risk-Taking: Big Data Evidence from 15 Credit Registers," Working paper, European Central Bank.

Altunbas, Y., S. Manganelli, and D. Marques-Ibanez (2017): "Realized bank risk during the great recession," *Journal of Financial Intermediation*, 32, 29 – 44.

Aramonte, S., S. J. Lee, and V. Stebunovs (2019): "Risk taking and low longer-term interest rates: Evidence from the U.S. syndicated term loan market," *Journal of Banking and Finance*, forthcoming.

Barth, J. R., J. Caprio, Gerard, and R. Levine (2013): "Bank Regulation and Supervision in 180 Countries from 1999 to 2011," Working Paper 18733, National Bureau of Economic Research.

Beltratti, A., and R. M. Stulz (2012): "The credit crisis around the globe: Why did some banks perform better?," *Journal of Financial Economics*, 105(1), 1 – 17.

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.

Calem, P., R. Correa, and S. J. Lee (2019): "Prudential policies and their impact on credit in the United States," *Journal of Financial Intermediation*, p. 100826.

Cerutti, E., R. Correa, E. Fiorentino, and E. Segalla (2017): "Changes in Prudential Policy Instruments - A New Cross-Country Database," *International Journal of Central Banking*, 13(2), 477–503.

Cohen, G., M. Friedrichs, K. Gupta, W. Hayes, S. J. Lee, B. Marsh, N. Mislang, M. Shaton, and M. Sicilian (2018): "The U.S. Syndicated Loan Market: Matching Data," Working paper.

Correia, S. (2016): "Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator," Working paper, Duke University.

Delis, M. D., and P. K. Staikouras (2011): "Supervisory Effectiveness and Bank Risk," *Review of Finance*, 15(3), 511–543.

Delis, M. D., P. K. Staikouras, and C. Tsoumas (2017): "Formal Enforcement Actions and Bank Behavior," *Management Science*, 63(4), 959–987.

Dell'Ariccia, G., L. Laeven, and R. Marquez (2014): "Real Interest Rates, Leverage, and Bank Risk-Taking," *Journal of Economic Theory*, 149, 65–99.

Dell'Ariccia, G., L. Laeven, and G. A. Suarez (2017): "Bank Leverage and Monetary Policy's Risk-Taking Channel: Evidence from the United States," *Journal of Finance*, 72(2), 613–654.

DeYoung, R., and G. Torna (2013): "Nontraditional banking activities and bank failures during the financial crisis," *Journal of Financial Intermediation*, 22(3), 397 – 421.

Fama, E. F., and K. R. French (1997): "Industry Costs of Equity," *Journal of Financial Economics*, 43(2), 153–193.

Flannery, M. J. (1998): "Using Market Information in Prudential Bank Supervision: A Review of the U.S. Empirical Evidence," *Journal of Money, Credit and Banking*, 30(3), 273–305.

Haselmann, R., S. Singla, and V. Vig (2019): "Supranational Supervision," Working paper, Goethe University and SAFE.

Ioannidou, V., S. Ongena, and J. Peydro (2015): "Monetary Policy, Risk-Taking and Pricing: Evidence from a Quasi-Natural Experiment," *Review of Finance*, 19(1), 95–144.

Ivashina, V. (2009): "Asymmetric information effects on loan spreads," *Journal of Financial Economics*, 92(2), 300 – 319.

Ivashina, V., and D. Scharfstein (2010): "Bank Lending During the Financial Crisis of 2008," *Journal of Financial Economics*, 97(3), 319–338.

Jessen, C., and D. Lando (2015): "Robustness of distance-to-default," *Journal of Banking and Finance*, 50, 493 – 505.

Jimenez, G., S. Ongena, J. Peydro, and J. Saurina (2014): "Hazardous Times for Monetary Policy: What do Twenty-Three Million Bank Loans Say about the Effects of Monetary Policy on Credit-Risk Taking?," *Econometrica*, 82(2), 463–505.

Karolyi, G. A., and A. G. Taboada (2015): "Regulatory Arbitrage and Cross-Border Bank Acquisitions," *Journal of Finance*, 70(6), 2395–2450.

Kashyap, A. K., and J. C. Stein (2000): "What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?," *American Economic Review*, 90(3), 407–428.

Khwaja, A. I., and A. Mian (2008): "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, 98(4), 1413–42.

Kim, S., M. C. Plosser, and J. A. Santos (2018): "Macroprudential policy and the revolving door of risk: Lessons from leveraged lending guidance," *Journal of Financial Intermediation*, 34, 17 – 31, Assessing Banking Regulation During the Obama Era.

Lee, S. J., L. Q. Liu, and V. Stebunovs (2019): "Risk-taking spillovers of U.S. monetary policy in the global market for U.S. dollar corporate loans," *Journal of Banking and Finance*, forthcoming.

Maddaloni, A., and J.-L. Peydro (2011): "Bank Risk-taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro-area and the U.S. Lending Standards," *Review of Financial Studies*, 24(6), 2121–2165.

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

Munves, D., D. Hamilton, and O. Gokbayrak (2009): "The Performance of EDFs since the Start of the Credit Crisis," Discussion paper, Moodys Analytics.

Nazeran, P., and D. Dwyer (2015): "Credit Risk Modeling of Public Firms: EDF9," Discussion paper, Moody's Analytics.

Pugachev, L. (2019): "The risk-shifting value of payout: Evidence from bank enforcement actions," *Journal of Banking and Finance*, p. 105595.

Rezende, M., and J. J. Wu (2013): "The Effects of Supervision on Bank Performance: Evidence from Discontinuous Examination Frequencies," Working paper, Board of Governors of the Federal Reserve System.

Wu, J. C., and F. D. Xia (2016): "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound," *Journal of Money, Credit and Banking*, 48(2-3), 253–291.

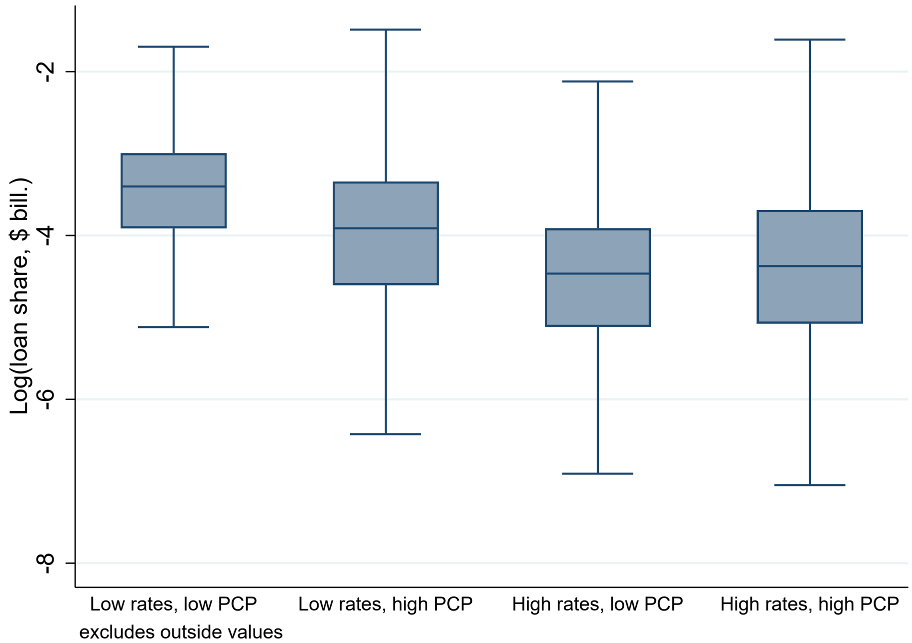

Figure 1: Loan shares in riskiest loans across different policy rates and prompt corrective power environments

Note. For the global sample, the figures shows box plots of loan amounts made to the riskiest borrowers across 4 U.S. policy rate and prompt corrective power (PCP) environments (Low rates, low prompt corrective power; Low rates, high prompt corrective power; High rates, low prompt corrective power; and High rates, high prompt corrective power). The riskiest loans are loans with EDFs in the top 25th percentile of the distribution. Low U.S. policy rates are rates in the bottom 25th percentile of the distribution and high U.S. policy rates are rates in the top 75th percentile. Low prompt corrective power characteristics are characteristics in the bottom 25th percentile of the distribution and high prompt corrective power characteristics are in the top 75th percentile. The figure suggests that while in high rate environments differences in loan amounts across low and high prompt corrective power environments are minimal, in low rate environments, loan amounts in low prompt corrective power environments are significantly larger than those in high prompt corrective power environments (the median in dollar terms in the first box plot is nearly twice the same measure in the second box plot). Note that the figure is for illustrative purposes and that it does not adequately reflect the regression analysis. For example, in the figure, we do not control for bank or borrower characteristics. For the non-U.S. borrower sample, the box plots are qualitatively very similar, and the differences between the last two box plots are notably smaller.

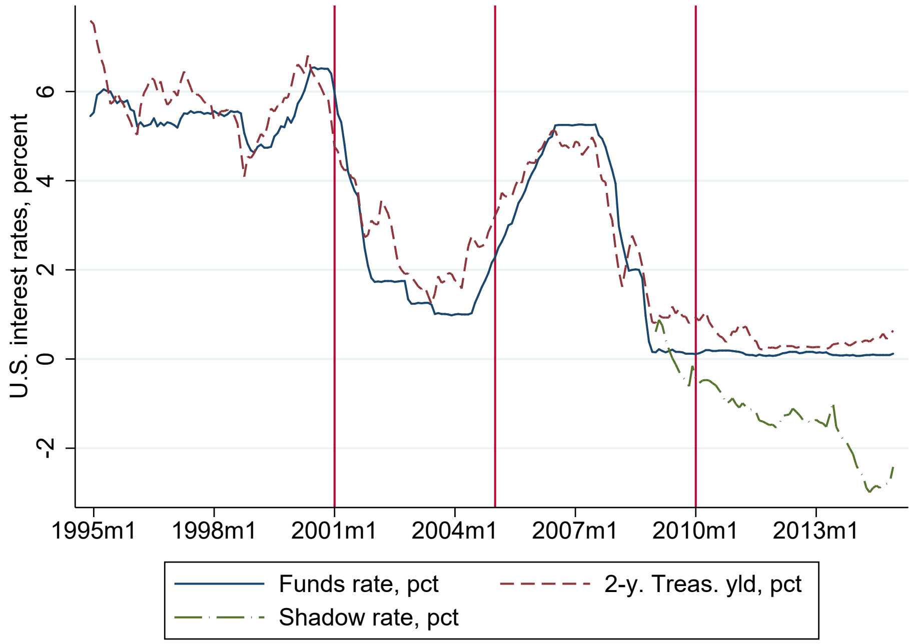

Figure 2: U.S. interest rates

Note. We capture U.S. monetary policy by various interest rates. The federal funds rates has been widely used in the literature. Because we rely on identification through heterogeneity, the federal funds rate being stuck at the zero lower bound does not appear to be an issue. Nevertheless, we consider other U.S. interest rates which exhibit more variation in the zero lower bound period. We also capture U.S. monetary policy by the 2-year U.S. Treasury yield, which reflects not only the spot federal funds rate of U.S. monetary policy but also a market-expected path of the federal funds rates (that is, funding costs) over the next two years. Moreover, we reestimate the regressions with U.S. monetary policy captured by the shadow rate from Wu and Xia (2016). The vertical lines denote the years of the 2nd, 3rd, and 4th surveys of Barth, Caprio, and Levine (2013) begin to apply, respectively.

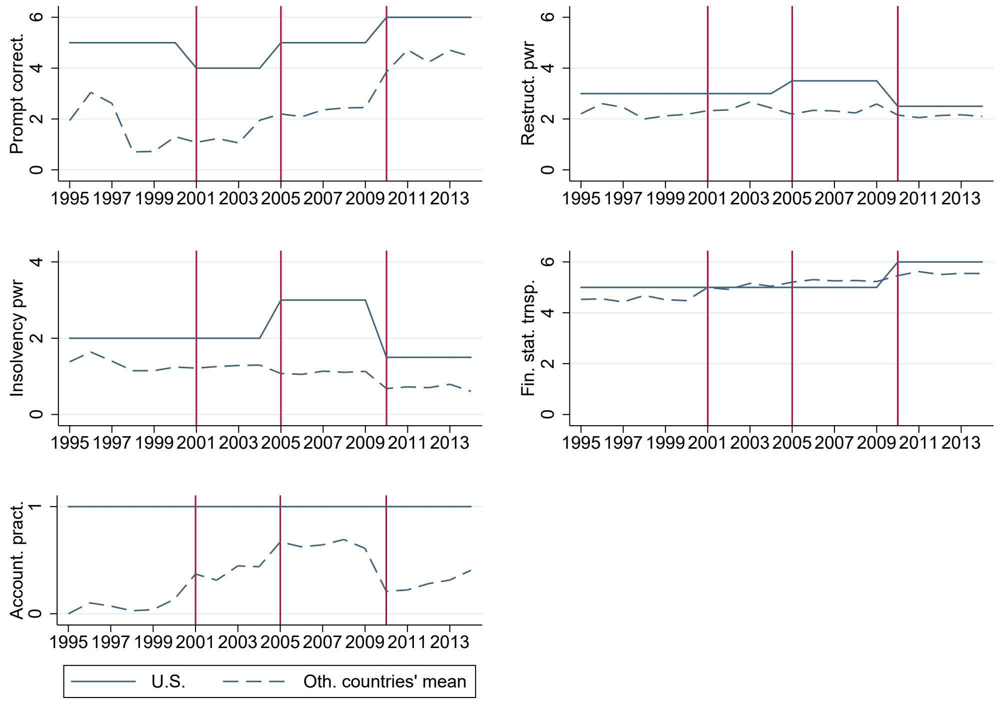

Figure 3: SRM characteristics of the sample countries

Note. For the global sample, the figure shows the simple averages of SRM characteristics that have statistically significant effects on ex ante credit risk taking (that is, θ_{ESR} is statistically significant) both in the 1995-2014 and 1995-2008 periods. The vertical lines denote the years of the 2nd, 3rd, and 4th surveys of Barth, Caprio, and Levine (2013) begin to apply, respectively. We cut the sample at 2014 because of fast-changing SRM characteristics, in particular for European banks, which account for about 40 percent of observations in the sample without U.S. borrowers. For the non-U.S. sample, the simple averages change more significantly over time, reflecting less stable SRM environments outside the United States.

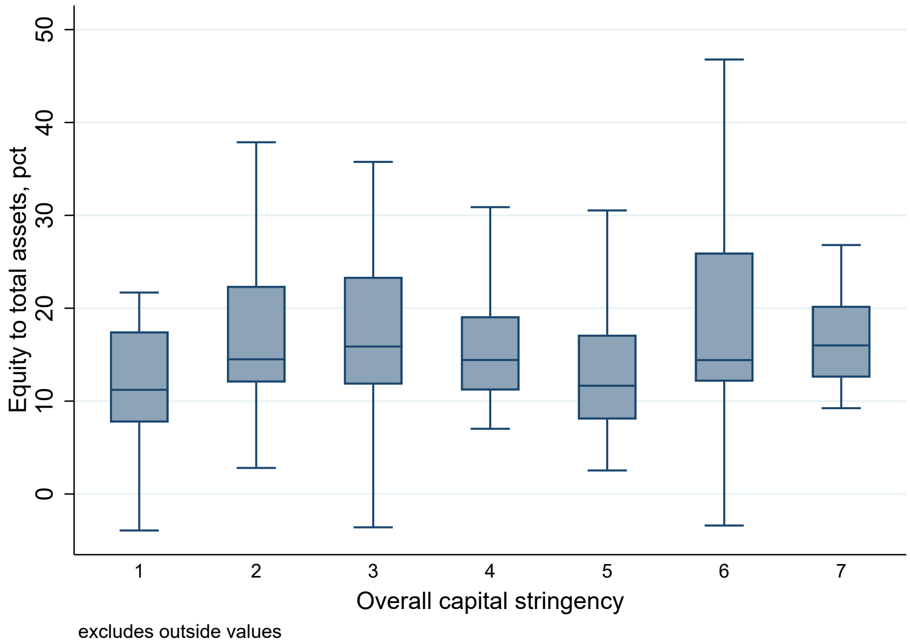

Figure 4: Capital ratios vs strigency of capital regulation at a banking system level

Note. For the global sample, the figures shows box plots for equity-to-total assets ratios by overall capital stringency at a banking system level for the 1995-2014 period for the sample countries (because of limited data availability and comparability we do not consider risk-based ratios). We construct capital ratios based on data from Moody's Analytics BankFocus. The data do not suggest positive association between capital ratios and overall capital stringency at a banking system level.

Table 1: SRM characteristics Barth, Caprio, and Levine (2013)

Potential mitigant	Description	Values*
Official Supervisory Action		
Prompt Corrective Power	Whether a law establishes predetermined levels of bank solvency deterioration that force automatic actions, such as intervention (more promptness in addressing problems).	0...6
Restructuring Power	Whether the supervisory authorities have the power to restructure and reorganize a troubled bank.	0...6
Declaring Insolvency Power	Whether the supervisory authorities have the power to declare a deeply troubled bank insolvent (the number of authorities with such power).	0...4
Supervisory Forbearance Discretion	Whether the supervisory authorities may engage in forbearance when confronted with violations of laws and regulations or other imprudent behavior (higher values indicate more supervisory discretion).	0...4
Court Involvement	The degree to which the court dominates the supervisory authority.	0...3
Loan Classification Stringency	The classification of loans in arrears as sub-standard, doubtful and loss.	Number
Provisioning Stringency	The minimum required provisions as loans become sub-standard, doubtful and loss.	Number
Diversification Index	Whether there are explicit, verifiable, quantifiable guidelines for asset diversification, and banks are allowed to make loans abroad.	0...2
Activity restrictions and Capital Regulation		
Securities Activities	The extent to which banks may engage in underwriting, brokering and dealing in securities, and all aspects of the mutual fund industry.	1...4
Insurance Activities	The extent to which banks may engage in insurance underwriting and selling.	1...4
Real Estate Activities	The extent to which banks may engage in real estate investment, development and management.	1...4
Overall Capital Stringency	Whether the capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined (greater stringency).	0...7
Memo: Basel III implementation	Implementation of Basel III regime, from Cerutti, Correa, Fiorentino, and Segalla (2017).	0...1
Private Monitoring and External Governance		
Certified Audit Required	Whether there is a compulsory external audit by a licensed or certified auditor.	0...1
Bank Accounting	Whether the income statement includes accrued or unpaid interest or principal on nonperforming loans and whether banks are required to produce consolidated financial statements (more informative bank accounts.)	0...4
Private Monitoring Index	Measures whether there incentives/ability for the private monitoring of firms, with higher values indicating more private monitoring (more informative private oversight).	0...12
Strength of External Audit	The effectiveness of external audits of banks.	0...7
Financial Statement Transparency	The transparency of bank financial statements practices (bank directors liable for providing detailed on and off balance sheet and income statement information).	0...6
Accounting Practices	The type of accounting practices used (IFRS or U.S. GAAP).	0...1

* Higher values indicate greater degree or higher quality, depending on the context.

Table 2: Lists of bank and borrower countries

Bank countries	Percentage of obs.	Borrower countries	Percentage of obs.
Panel A. Global sample			
United States	33.20	United States	41.83
Japan	11.21	India	15.97
United Kingdom	9.44	Hong Kong	5.76
Taiwan	8.29	Korea (South)	5.60
France	7.28	China	5.49
Germany	6.75	Philippines	2.41
Canada	3.68	United Kingdom	2.25
China	3.07	Turkey	2.20
Korea (South)	2.05	Taiwan	2.06
Netherlands	2.03	Malaysia	1.58
Other 30 countries	13.00	Other 42 countries	14.85
Panel B. Non-U.S. sample			
Taiwan	14.67	India	27.53
Japan	14.64	Hong Kong	9.99
United Kingdom	11.03	Korea (South)	9.65
France	9.51	China	9.53
Germany	8.61	Philippines	4.10
United States	8.37	United Kingdom	3.88
China	5.43	Turkey	3.73
Korea (South)	3.43	Taiwan	3.63
India	3.17	Malaysia	2.62
Singapore	2.73	Singapore	1.92
Other 30 countries	18.41	Other 41 countries	23.42

Note. Panel A is based on the sample in Table 5 col 1 and panel B on the sample in Table 5 col 5.

Table 3: Descriptive statistics for the global and non-U.S. samples

	Obs.	mean	st. dev.	25th pct	50th pct	75th pct
Panel A. Global factor (*that varies by time*)						
shadow rate, pct	10050	1.75	3.06	-1.27	1.81	4.99
Panel B. Global sample						
Characteristics that vary by loan share						
log(loan share, $ bill.)	10050	-3.91	1.07	-4.61	-3.91	-3.21
log(EDF, pct)	10050	-0.09	1.29	-0.95	-0.06	0.87
SRM characteristics that vary by time and bank country						
Prompt Corrective Power	8810	3.67	2.51	0.00	5.00	6.00
Declaring Insolvency Power	9160	1.39	0.78	1.00	1.50	2.00
Supervisory Forbearance Discretion	8451	1.59	0.79	1.00	1.00	2.00
Provisioning Stringency	3181	157.68	30.90	160.00	165.00	165.00
Real est. restr.	9454	2.91	1.25	1.00	3.00	4.00
Securit. restr.	9451	2.06	0.88	1.00	2.00	3.00
Bank Accounting	9598	3.58	0.56	3.00	4.00	4.00
Financial Statement Transparency	9557	5.26	0.71	5.00	5.00	6.00
Accounting Practices	8979	0.64	0.48	0.00	1.00	1.00
Panel C. Non-U.S. sample						
Characteristics that vary by loan share						
log(loan share, $ bill.)	5677	-4.07	1.03	-4.66	-4.09	-3.43
log(EDF, pct)	5677	0.16	1.19	-0.53	0.27	1.07
SRM characteristics that vary by time and bank country						
Prompt Corrective Power	4766	3.23	2.66	0.00	4.00	6.00
Declaring Insolvency Power	5108	1.15	0.76	1.00	1.00	2.00
Supervisory Forbearance Discretion	4493	1.70	0.81	1.00	2.00	2.00
Provisioning Stringency	1929	152.48	35.77	160.00	160.00	165.00
Real est. restr.	5283	2.77	1.28	1.00	3.00	4.00
Securit. restr.	5280	1.92	0.91	1.00	2.00	3.00
Bank Accounting	5389	3.45	0.57	3.00	3.00	4.00
Financial Statement Transparency	5348	5.23	0.75	5.00	5.00	6.00
Accounting Practices	4960	0.51	0.50	0.00	1.00	1.00
Panel D. Global sample, shadow bank regressions						
Characteristics that vary by syndicate						
loan share of nonbanks in a syndicate, pct	2232	6.98	12.26	0.00	0.00	9.62
$\overline{\textit{ppt cor. pwr}}$	2231	3.35	1.81	2.00	3.67	5.00
$\overline{\textit{insol. pwr}}$	2231	1.42	0.69	1.00	1.47	2.00

Note. The non-U.S. sample in the panel C excludes U.S. borrowers. The number of observations varies by row because SRM characteristics from Barth, Caprio, and Levine (2013) are not available for all sample countries for all years. In panel D, for each syndicate, prompt corrective power is a weighted average of this characteristic in countries where agent and arranger banks of that syndicate are headquartered.

Table 4: Summary of results

Potential mitigant	Signs of θ_{ES} Hypothesized	Signs of θ_{ES} Estimated	Signs of θ_{ESR} Hypothesized	Signs of θ_{ESR} Estimated
Official Supervision				
Prompt Corrective Power	Gen. mitig. of	−	Mitig. of	+
Restructuring Power	risk-taking:		risk-taking	
Declaring Insolvency Power	$\theta_{ES} < 0$; but	−	chan.:	+
Supervisory Forbearance Discretion	$\theta_{ES} > 0$	+	$\theta_{ESR} > 0$; but	−
Court Involvement	possible		$\theta_{ESR} < 0$	
Loan Classification Stringency			possible	
Provisioning Stringency		−		+
Diversification Requirement				
Activity restrictions and Capital Regulation				
Real est. restr.	Gen. mitig. of		Mitig. of	+
Insurance restr.	risk-taking:		risk-taking	
Securit. restr.	$\theta_{ES} < 0$; but	−	chan.:	+
Overall Capital Stringency	$\theta_{ES} > 0$		$\theta_{ESR} > 0$; but	
Basel III	possible		$\theta_{ESR} < 0$	+
			possible	
Private Monitoring and External Governance				
Certified Audit Required				
Bank Accounting	Gen. mitig. of	−	Mitig. of	+
Private Monitoring	risk-taking:		risk-taking	
Strength of External Audit	$\theta_{ES} < 0$		chan.:	
Financial Statement Transparency		−	$\theta_{ESR} > 0$	+
Accounting Practices		−		+

Note. Signs are shown only for the coefficients that are statististically significant in at least 2 out of 4 specifications in either the global sample or the non-U.S. sample or both. The SRM characteristics in bold have statistically significant mitigating effects in the regressions estimated over the 1995-2014 and 1995-2008 periods.

Table 5: Regressions for the baseline

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.063	0.087	0.164	0.206	0.252	0.248	0.212	0.222
	(0.846)	(0.921)	(1.404)	(1.341)	(1.444)	(1.272)	(1.253)	(1.075)
log(EDF) × shd rate	-0.037**	-0.049**	-0.060**	-0.076*	-0.101**	-0.105**	-0.095**	-0.109*
	(-2.247)	(-2.218)	(-2.060)	(-1.899)	(-2.154)	(-1.983)	(-2.004)	(-1.827)
Num. of observ.	10050	7045	6968	6895	5677	3472	3464	3435
R-sq. adj.	0.78	0.72	0.69	0.66	0.78	0.70	0.69	0.67
RMSE	0.50	0.58	0.61	0.65	0.48	0.60	0.60	0.63
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effect. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: Regressions for ppt cor. pwr

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.145*	0.220**	0.344***	0.369***	0.374**	0.476***	0.483***	0.460**
	(1.889)	(2.261)	(2.985)	(2.649)	(2.430)	(2.700)	(2.754)	(2.349)
log(EDF) × ppt cor. pwr	-0.014**	-0.021***	-0.019**	-0.018**	-0.022***	-0.030***	-0.029***	-0.028***
	(-2.448)	(-2.825)	(-2.534)	(-2.521)	(-2.869)	(-3.086)	(-2.971)	(-2.912)
log(EDF) × shd rate	-0.056***	-0.080***	-0.105***	-0.113***	-0.136***	-0.161***	-0.162***	-0.166***
	(-3.023)	(-3.278)	(-3.240)	(-2.890)	(-3.060)	(-3.132)	(-3.077)	(-2.751)
log(EDF) × ppt cor. pwr × shd rate	0.003**	0.005***	0.005***	0.005***	0.005***	0.007***	0.007***	0.007***
	(2.150)	(2.777)	(2.704)	(2.640)	(2.878)	(2.750)	(2.788)	(2.660)
Num. of observ.	8770	6093	6001	5934	4732	2840	2818	2797
R-sq. adj.	0.77	0.70	0.67	0.62	0.78	0.68	0.67	0.64
RMSE	0.51	0.61	0.64	0.69	0.48	0.61	0.62	0.64
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 7: Summary of marginal effects for the baseline and prompt corrective power regressions

	median log(EDF)	75th pct log(EDF)	95th pct log(EDF)
Panel A. Marginal effects in the baseline regressions			
Δ loan share, $ mill. / Δ funds rate | Prompt correct. pwr at 4; non-U.S. borrowers (see eq. 2)			
Marginal effect, $ mill.	1.1	4.3	7.1
Marginal effect, pct of median amount	7.0	27.5	45.2
Panel B. Marginal effects in the prompt corrective power regressions			
Δ loan share, $ mill. / Δ funds rate | Prompt correct. pwr at 4; non-U.S. borrowers (see eq. 2)			
Marginal effect, $ mill.	1.4	5.4	9.0
Marginal effect, pct of median amount	8.8	34.8	57.2
Panel C. Effect of higher prompt corrective power on the marginal effects			
Δ (Δ loan share, $ mill. / Δ funds rate) | Δ Prompt correct. pwr up from 4 to 6 (see eq. 3)			
Change in marginal effect, $ mill.	-0.4	-1.7	-2.7

Note. In panel A, calculations are based on the estimation results in columns (4) and (8) of the base line table. Calculations assume a standard deviation decrease in the federal funds rate. For reference, the median loan size is nearly $16 million (taken to be the same for all borrowers and non-U.S. borrowers, for comparison transparency. In panel B and C, calculations are based on the estimation results in column (8) of the prompt corrective power table. Calculations assume a standard deviation decrease in the federal funds rate and an increase in the prompt corrective power characteristic from its median (4) to the 75th percentile (6).

Table 8: Regressions for insol. pwr

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.152*	0.203**	0.276**	0.319**	0.318**	0.384*	0.364*	0.358*
	(1.932)	(2.010)	(2.181)	(2.139)	(1.996)	(1.970)	(1.974)	(1.707)
log(EDF) × insol. pwr	-0.060***	-0.077***	-0.070**	-0.064**	-0.062**	-0.081**	-0.073*	-0.072*
	(-3.009)	(-2.863)	(-2.484)	(-2.266)	(-2.167)	(-2.111)	(-1.917)	(-1.932)
log(EDF) × shd rate	-0.059***	-0.080***	-0.093***	-0.106**	-0.125***	-0.140**	-0.134**	-0.143**
	(-3.123)	(-3.188)	(-2.725)	(-2.596)	(-2.848)	(-2.598)	(-2.548)	(-2.326)
log(EDF) × insol. pwr × shd rate	0.014**	0.020***	0.019***	0.018**	0.017**	0.019*	0.018*	0.019*
	(2.580)	(2.767)	(2.613)	(2.397)	(2.246)	(1.802)	(1.751)	(1.766)
Num. of observ.	9133	6301	6205	6139	5087	3038	3015	2990
R-sq. adj.	0.77	0.71	0.67	0.62	0.78	0.68	0.67	0.64
RMSE	0.51	0.60	0.64	0.68	0.48	0.61	0.62	0.65
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 9: Regressions for sup. foreb.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.038	0.041	0.163	0.217	0.242	0.252	0.246	0.250
	(0.500)	(0.430)	(1.427)	(1.608)	(1.577)	(1.362)	(1.405)	(1.234)
log(EDF) × sup. foreb.	0.034***	0.056***	0.048***	0.048***	0.038**	0.065***	0.062**	0.057**
	(2.699)	(3.257)	(2.743)	(2.841)	(2.456)	(2.800)	(2.541)	(2.490)
log(EDF) × shd rate	-0.029	-0.033	-0.053*	-0.070*	-0.097**	-0.108**	-0.100**	-0.112*
	(-1.572)	(-1.362)	(-1.735)	(-1.906)	(-2.252)	(-2.101)	(-1.982)	(-1.884)
log(EDF) × sup. foreb. × shd rate	-0.008**	-0.015***	-0.015***	-0.014***	-0.011**	-0.015**	-0.016**	-0.015**
	(-2.199)	(-3.062)	(-3.161)	(-3.158)	(-2.401)	(-2.332)	(-2.383)	(-2.341)
Num. of observ.	8408	5905	5807	5745	4459	2722	2702	2681
R-sq. adj.	0.77	0.69	0.65	0.60	0.77	0.66	0.65	0.62
RMSE	0.52	0.61	0.65	0.70	0.49	0.62	0.63	0.66
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 10: Regressions for stat. trnsp

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.257**	0.384***	0.406**	0.477**	0.546**	0.624**	0.561**	0.592**
	(2.265)	(2.638)	(2.555)	(2.354)	(2.534)	(2.283)	(2.334)	(2.032)
log(EDF) × stat. trnsp	-0.033**	-0.050**	-0.038*	-0.043**	-0.054**	-0.061**	-0.056**	-0.059**
	(-1.999)	(-2.398)	(-1.865)	(-2.006)	(-2.220)	(-2.140)	(-2.018)	(-2.056)
log(EDF) × shd rate	-0.079***	-0.107***	-0.117***	-0.137***	-0.177***	-0.201***	-0.186***	-0.212***
	(-3.028)	(-2.987)	(-2.916)	(-2.651)	(-3.243)	(-2.902)	(-2.976)	(-2.731)
log(EDF) × stat. trnsp × shd rate	0.007*	0.010*	0.009*	0.010*	0.014**	0.016**	0.015**	0.017**
	(1.839)	(1.831)	(1.691)	(1.828)	(2.369)	(2.338)	(2.278)	(2.455)
Num. of observ.	9538	6643	6549	6488	5337	3255	3225	3206
R-sq. adj.	0.78	0.71	0.68	0.64	0.78	0.68	0.67	0.65
RMSE	0.51	0.60	0.63	0.67	0.48	0.61	0.62	0.64
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 11: Regressions for accnt pract.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.079	0.142	0.209*	0.262	0.282	0.348	0.303	0.327
	(1.026)	(1.424)	(1.736)	(1.629)	(1.577)	(1.582)	(1.620)	(1.379)
log(EDF) × accnt pract.	-0.019	-0.038	-0.036	-0.037	-0.053*	-0.082**	-0.080**	-0.083**
	(-0.825)	(-1.503)	(-1.357)	(-1.418)	(-1.835)	(-2.120)	(-2.089)	(-2.150)
log(EDF) × shd rate	-0.045**	-0.071***	-0.084***	-0.105**	-0.136***	-0.155**	-0.137**	-0.162**
	(-2.467)	(-2.824)	(-2.713)	(-2.411)	(-2.859)	(-2.539)	(-2.585)	(-2.409)
log(EDF) × accnt pract. × shd rate	0.006	0.015*	0.014*	0.014*	0.025***	0.033***	0.032***	0.033***
	(0.928)	(1.964)	(1.852)	(1.811)	(3.384)	(3.009)	(2.775)	(2.835)
Num. of observ.	8937	6175	6081	6022	4939	2935	2915	2895
R-sq. adj.	0.77	0.69	0.65	0.60	0.77	0.65	0.65	0.62
RMSE	0.52	0.61	0.65	0.69	0.49	0.64	0.64	0.67
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 12: Regressions for prompt corrective power vs insol. pwr

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.175**	0.255***	0.369***	0.389***	0.384**	0.498***	0.499***	0.477**
	(2.264)	(2.609)	(3.147)	(2.765)	(2.457)	(2.735)	(2.807)	(2.381)
log(EDF) × ppt cor. pwr	-0.006	-0.012	-0.010	-0.011	-0.018***	-0.025***	-0.025***	-0.024***
	(-1.060)	(-1.557)	(-1.404)	(-1.426)	(-2.728)	(-3.341)	(-3.279)	(-3.198)
log(EDF) × insol. pwr	-0.051**	-0.061*	-0.056*	-0.049	-0.030	-0.049*	-0.046*	-0.043
	(-2.146)	(-1.965)	(-1.729)	(-1.453)	(-1.346)	(-1.819)	(-1.727)	(-1.594)
log(EDF) × shd rate	-0.064***	-0.092***	-0.115***	-0.122***	-0.141***	-0.170***	-0.170***	-0.174***
	(-3.471)	(-3.701)	(-3.539)	(-3.109)	(-3.204)	(-3.306)	(-3.290)	(-2.929)
log(EDF) × ppt cor. pwr × shd rate	0.001	0.002	0.002	0.002	0.004**	0.005**	0.005**	0.005**
	(0.702)	(1.393)	(1.341)	(1.332)	(2.377)	(2.404)	(2.474)	(2.246)
log(EDF) × insol. pwr × shd rate	0.013**	0.017**	0.016**	0.015*	0.011*	0.015*	0.015*	0.015*
	(2.298)	(2.231)	(1.988)	(1.750)	(1.767)	(1.899)	(1.844)	(1.823)
Num. of observ.	8727	6073	5981	5914	4692	2821	2800	2778
R-sq. adj.	0.77	0.71	0.67	0.62	0.78	0.68	0.67	0.64
RMSE	0.51	0.60	0.64	0.69	0.48	0.61	0.62	0.64
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table 13: Regressions for prompt corrective power vs stat. trnsp

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.460***	0.637***	0.665***	0.713***	0.796***	0.873***	0.849***	0.824***
	(3.074)	(3.315)	(3.259)	(3.075)	(3.615)	(3.660)	(3.764)	(3.038)
log(EDF) × ppt cor. pwr	-0.016***	-0.023***	-0.020***	-0.020***	-0.026***	-0.034***	-0.033***	-0.031***
	(-2.949)	(-3.427)	(-3.031)	(-3.014)	(-3.770)	(-3.920)	(-3.695)	(-3.635)
log(EDF) × stat. trnsp	-0.054**	-0.071**	-0.057**	-0.060**	-0.075***	-0.069***	-0.064**	-0.063**
	(-2.361)	(-2.574)	(-1.996)	(-2.073)	(-3.000)	(-2.729)	(-2.606)	(-2.349)
log(EDF) × shd rate	-0.122***	-0.162***	-0.176***	-0.189***	-0.239***	-0.268***	-0.267***	-0.277***
	(-3.550)	(-3.471)	(-3.304)	(-3.156)	(-4.136)	(-3.976)	(-3.953)	(-3.489)
log(EDF) × ppt cor. pwr × shd rate	0.003**	0.005***	0.005***	0.005***	0.006***	0.008***	0.008***	0.008***
	(2.525)	(3.194)	(3.078)	(3.006)	(3.642)	(3.310)	(3.317)	(3.200)
log(EDF) × stat. trnsp × shd rate	0.011**	0.014**	0.013*	0.013**	0.018***	0.019***	0.019***	0.019***
	(2.380)	(2.228)	(1.931)	(2.028)	(3.130)	(2.818)	(2.812)	(2.735)
Num. of observ.	8733	6074	5982	5915	4706	2834	2812	2791
R-sq. adj.	0.77	0.70	0.66	0.62	0.78	0.68	0.67	0.64
RMSE	0.51	0.61	0.64	0.69	0.48	0.61	0.62	0.64
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table 14: Regressions for prompt corrective power vs accnt pract.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.133^{+}	0.222**	0.340***	0.372**	0.385**	0.498**	0.495***	0.487**
	(1.645)	(2.215)	(2.871)	(2.562)	(2.268)	(2.553)	(2.641)	(2.234)
log(EDF) × ppt cor. pwr	-0.017***	-0.024***	-0.021**	-0.020**	-0.023***	-0.029***	-0.029**	-0.026**
	(-2.716)	(-2.988)	(-2.536)	(-2.471)	(-2.886)	(-2.729)	(-2.546)	(-2.431)
log(EDF) × accnt pract.	0.026	0.033	0.021	0.018	0.023	0.001	0.004	-0.006
	(0.933)	(0.789)	(0.500)	(0.451)	(0.493)	(0.023)	(0.065)	(-0.098)
log(EDF) × shd rate	-0.055***	-0.089***	-0.116***	-0.129***	-0.163***	-0.192***	-0.188***	-0.202***
	(-2.815)	(-3.369)	(-3.430)	(-3.114)	(-3.590)	(-3.466)	(-3.455)	(-3.204)
log(EDF) × ppt cor. pwr × shd rate	0.003*	0.005**	0.005**	0.004**	0.005**	0.006*	0.007**	0.006*
	(1.972)	(2.546)	(2.207)	(2.027)	(2.290)	(1.972)	(2.096)	(1.862)
log(EDF) × accnt pract. × shd rate	-0.003	-0.001	0.001	0.002	0.009	0.014	0.014	0.016
	(-0.586)	(-0.138)	(0.156)	(0.214)	(0.859)	(0.967)	(0.921)	(1.102)
Num. of observ.	8090	5590	5496	5430	4266	2497	2483	2460
R-sq. adj.	0.76	0.68	0.62	0.57	0.76	0.63	0.63	0.60
RMSE	0.52	0.63	0.67	0.72	0.49	0.65	0.65	0.68
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table 15: Prompt Corrective Power components from Barth, Caprio, and Levine (2013)

Potential mitigant	Description	Values*
Early automatic intervention	Does the law establish pre-determined levels of solvency deterioration which forces automatic actions such as intervention?	0...1
Cease and desist order	Are there any mechanisms of cease-desist type orders whose infraction leads to automatic imposition of civil and penal sanctions on banks directors and managers?	0...1
Force provisions	Can the supervisory agency order directors or management to constitute provisions to cover actual or potential losses?	0...1
Suspension of dividends	Can the supervisory agency suspend director's decision to distribute: Dividends	0...1
Suspension of bonuses	Can the supervisory agency suspend director's decision to distribute: Bonuses	0...1
Suspension of management fees	Can the supervisory agency suspend director's decision to distribute: Management fees	0...1
Force reorganization	Can supervisors force banks to change internal organizational structure?	0...1

* 1 indicates that the authority has a given power.

Table 16: Regressions for earl. interv.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.122	0.192**	0.274**	0.312**	0.328**	0.405**	0.384**	0.377*
	(1.620)	(1.996)	(2.321)	(2.047)	(2.073)	(2.151)	(2.215)	(1.828)
log(EDF) × earl. interv.	-0.056**	-0.098***	-0.086**	-0.087**	-0.099***	-0.152***	-0.143***	-0.138***
	(-2.027)	(-2.719)	(-2.366)	(-2.417)	(-2.731)	(-3.422)	(-3.288)	(-3.202)
log(EDF) × shd rate	-0.049***	-0.073***	-0.089***	-0.101**	-0.123***	-0.142***	-0.138***	-0.146**
	(-2.819)	(-3.081)	(-2.872)	(-2.459)	(-2.782)	(-2.710)	(-2.765)	(-2.413)
log(EDF) × earl. interv. × shd rate	0.012*	0.024***	0.023***	0.023***	0.026***	0.035***	0.036***	0.034***
	(1.697)	(2.776)	(2.657)	(2.671)	(2.838)	(3.033)	(3.106)	(2.965)
Num. of observ.	9551	6645	6553	6492	5339	3244	3216	3197
R-sq. adj.	0.78	0.71	0.68	0.64	0.78	0.68	0.68	0.65
RMSE	0.51	0.59	0.63	0.67	0.48	0.61	0.62	0.64
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 17: Regressions for cease order

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.119	0.191*	0.270**	0.328**	0.303*	0.391*	0.383**	0.365*
	(1.463)	(1.819)	(2.032)	(2.106)	(1.855)	(1.971)	(1.979)	(1.683)
log(EDF) × cease order	-0.061*	-0.110***	-0.089**	-0.098**	-0.062	-0.110**	-0.102*	-0.092*
	(-1.804)	(-2.968)	(-2.280)	(-2.363)	(-1.525)	(-2.082)	(-1.945)	(-1.861)
log(EDF) × shd rate	-0.051***	-0.074***	-0.089**	-0.105**	-0.120***	-0.145***	-0.141**	-0.148**
	(-2.684)	(-2.953)	(-2.584)	(-2.565)	(-2.668)	(-2.650)	(-2.550)	(-2.339)
log(EDF) × cease order × shd rate	0.015**	0.027***	0.024**	0.026**	0.017	0.032**	0.031**	0.030**
	(2.176)	(2.956)	(2.451)	(2.478)	(1.565)	(2.169)	(2.114)	(2.104)
Num. of observ.	9191	6328	6230	6164	5143	3064	3038	3014
R-sq. adj.	0.77	0.70	0.67	0.62	0.78	0.68	0.67	0.64
RMSE	0.51	0.61	0.64	0.68	0.48	0.62	0.62	0.65
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 18: Regressions for susp. divid.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.185**	0.273**	0.353**	0.397**	0.504***	0.649***	0.607***	0.602***
	(2.091)	(2.210)	(2.548)	(2.524)	(3.127)	(3.260)	(3.078)	(2.794)
log(EDF) × susp. divid.	-0.118**	-0.176**	-0.158**	-0.153**	-0.257***	-0.360***	-0.316***	-0.323***
	(-2.172)	(-2.210)	(-2.109)	(-2.069)	(-3.475)	(-3.660)	(-3.158)	(-3.257)
log(EDF) × shd rate	-0.072***	-0.094***	-0.109***	-0.123***	-0.167***	-0.196***	-0.188***	-0.198***
	(-3.407)	(-3.233)	(-2.973)	(-2.901)	(-3.821)	(-3.675)	(-3.372)	(-3.173)
log(EDF) × susp. divid. × shd rate	0.034**	0.042**	0.039**	0.038**	0.063***	0.077***	0.072***	0.074***
	(2.458)	(2.252)	(2.114)	(2.091)	(3.322)	(3.169)	(2.913)	(2.997)
Num. of observ.	9151	6294	6196	6131	5112	3037	3010	2987
R-sq. adj.	0.77	0.70	0.67	0.62	0.78	0.68	0.67	0.64
RMSE	0.51	0.61	0.64	0.69	0.48	0.62	0.62	0.65
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects.
Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 19: Regressions for susp. bonus.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.131	0.172	0.243*	0.300**	0.419***	0.499***	0.485***	0.468**
	(1.640)	(1.548)	(1.822)	(1.985)	(2.802)	(2.822)	(2.724)	(2.335)
log(EDF) × susp. bonus.	-0.067	-0.075	-0.046	-0.054	-0.191***	-0.216***	-0.198***	-0.191***
	(-1.638)	(-1.494)	(-0.948)	(-1.107)	(-3.367)	(-3.463)	(-3.095)	(-3.013)
log(EDF) × shd rate	-0.052***	-0.071**	-0.085**	-0.101**	-0.148***	-0.170***	-0.166***	-0.173***
	(-2.678)	(-2.580)	(-2.349)	(-2.410)	(-3.499)	(-3.397)	(-3.168)	(-2.882)
log(EDF) × susp. bonus. × shd rate	0.013	0.019	0.016	0.017	0.048***	0.056***	0.054***	0.053***
	(1.282)	(1.521)	(1.278)	(1.376)	(3.403)	(3.376)	(3.192)	(3.135)
Num. of observ.	9151	6294	6196	6131	5112	3037	3010	2987
R-sq. adj.	0.77	0.70	0.66	0.62	0.78	0.68	0.67	0.64
RMSE	0.51	0.61	0.64	0.69	0.48	0.62	0.62	0.65
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects.
Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 20: Regressions for susp. fees

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.303	0.410*	0.630**	0.644**	0.610**	0.795***	0.821***	0.827***
	(1.654)	(1.858)	(2.590)	(2.443)	(2.458)	(3.304)	(3.314)	(3.085)
log(EDF) × susp. fees	-0.065	-0.058	-0.039	-0.040	-0.187***	-0.178**	-0.177**	-0.180**
	(-1.186)	(-0.835)	(-0.540)	(-0.555)	(-2.925)	(-2.496)	(-2.480)	(-2.518)
log(EDF) × shd rate	-0.077*	-0.117**	-0.174***	-0.175***	-0.181***	-0.228***	-0.254***	-0.254***
	(-1.670)	(-2.117)	(-2.809)	(-2.618)	(-2.644)	(-3.147)	(-3.363)	(-3.077)
log(EDF) × susp. fees × shd rate	0.011	0.012	0.010	0.011	0.042***	0.041**	0.041**	0.042**
	(0.830)	(0.710)	(0.605)	(0.625)	(2.629)	(2.076)	(2.056)	(2.103)
Num. of observ.	5895	4053	3995	3962	3357	2094	2084	2071
R-sq. adj.	0.75	0.69	0.64	0.61	0.77	0.68	0.68	0.66
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.58	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 21: Regressions for prompt corrective power

	Global sample			
	(1)	(2)	(3)	(4)
log(EDF)	-0.242	-0.647	-0.536	-0.176
	(-0.439)	(-1.065)	(-0.677)	(-0.112)
$\overline{\textit{ppt cor. pwr}}$	0.982***	0.668***	0.542**	1.029***
	(4.928)	(2.747)	(2.020)	(2.735)
log(EDF) × $\overline{\textit{ppt cor. pwr}}$	0.525***	0.460***	0.325*	0.518+
	(3.694)	(3.142)	(1.896)	(1.645)
log(EDF) × shd rate	0.444*	0.668***	1.038***	0.433
	(1.827)	(2.745)	(3.072)	(0.949)
$\overline{\textit{ppt cor. pwr}}$ × shd rate	-0.189***	-0.096*	-0.112	-0.205**
	(-3.358)	(-1.793)	(-1.488)	(-2.289)
log(EDF) × $\overline{\textit{ppt cor. pwr}}$ × shd rate	-0.101+	-0.129**	-0.167**	-0.068
	(-1.651)	(-2.140)	(-2.245)	(-0.698)
Num. of observ.	2231	2220	1689	1205
R-sq. adj.	0.08	0.18	0.21	0.32
RMSE	11.79	11.11	11.15	10.43
Borr. country FE	N	Y	N	Y
Borr. industry FE	N	Y	Y	N
Time FE (TFE)	Y	Y	N	N
Borr. country TFE	N	N	Y	N
Borr. industry TFE	N	N	N	Y

t statistics in parentheses
Note. Errors clustered by month.
$^{+}$ $p < 0.11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Appendix. Supporting regressions and robustness checks

Select SRM regressions for the 1995-2014 period

Table A1: Barth, Caprio, and Levine (2013)'s surveys

Survey	Publication year	Reference year	Number of countries	Number of questions	Range of years the survey applied to
I	1999	1999	118	> 300	1995-2000
II	2003	2002	151	> 400	2001-04
III	2007	2006	142	> 400	2005-09
IV	2012	2011	125	> 400	2010-14

Note. In spirit of Karolyi and Taboada (2015), we apply the characteristics from a given survey to a certain range of years. For example, we apply the characteristics from the 1999 survey for observations from 1995 through 2000. Because some of the characteristics might have been in effect for some time before the year of a given survey, we apply that those characteristics beginning the year before the survey year.

Table A2: Regressions for prov. str.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.120	0.962	1.658	1.658	0.741	3.542**	3.681**	3.681**
	(0.151)	(0.411)	(0.681)	(0.681)	(0.942)	(2.013)	(2.005)	(2.003)
log(EDF) × prov. str.	0.000	-0.004	-0.007	-0.007	-0.003	-0.019*	-0.020*	-0.020*
	(0.051)	(-0.305)	(-0.499)	(-0.498)	(-0.593)	(-1.843)	(-1.843)	(-1.841)
log(EDF) × shd rate	-0.132	-0.364	-0.509	-0.509	-0.273	-0.877**	-0.905**	-0.905**
	(-0.755)	(-0.776)	(-1.039)	(-1.038)	(-1.564)	(-2.437)	(-2.407)	(-2.405)
log(EDF) × prov. str. × shd rate	0.001	0.002	0.003	0.003	0.001	0.005**	0.005**	0.005**
	(0.640)	(0.678)	(0.868)	(0.867)	(1.200)	(2.235)	(2.216)	(2.214)
Num. of observ.	2950	1805	1759	1729	1776	887	886	869
R-sq. adj.	0.63	0.33	0.02	-0.19	0.65	0.09	-0.08	-0.41
RMSE	0.65	0.94	1.14	1.26	0.62	1.09	1.19	1.36
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A3: Regressions for r. est. rest.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.085	0.147	0.214*	0.266*	0.285*	0.366*	0.322*	0.343
	(1.101)	(1.475)	(1.789)	(1.678)	(1.683)	(1.718)	(1.695)	(1.491)
log(EDF) × r. est. rest.	-0.006	-0.014	-0.009	-0.010	-0.016	-0.029*	-0.022	-0.027
	(-0.787)	(-1.546)	(-0.937)	(-1.080)	(-1.430)	(-1.801)	(-1.418)	(-1.649)
log(EDF) × shd rate	-0.046***	-0.071***	-0.085***	-0.099**	-0.118**	-0.141**	-0.132**	-0.148**
	(-2.677)	(-3.039)	(-2.786)	(-2.377)	(-2.561)	(-2.445)	(-2.469)	(-2.230)
log(EDF) × r. est. rest. × shd rate	0.003	0.007**	0.006**	0.006**	0.006**	0.009**	0.009**	0.010**
	(1.395)	(2.338)	(2.345)	(2.309)	(2.111)	(2.248)	(2.279)	(2.413)
Num. of observ.	9429	6571	6477	6418	5268	3208	3182	3161
R-sq. adj.	0.78	0.72	0.68	0.64	0.78	0.69	0.68	0.66
RMSE	0.51	0.59	0.63	0.67	0.48	0.61	0.61	0.64
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A4: Regressions for secur. rest.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.107	0.186*	0.253**	0.308*	0.305*	0.400*	0.370*	0.382
	(1.377)	(1.842)	(2.099)	(1.898)	(1.779)	(1.878)	(1.907)	(1.651)
log(EDF) × secur. rest.	-0.016	-0.035**	-0.029*	-0.030*	-0.027	-0.058**	-0.055*	-0.056**
	(-1.283)	(-2.231)	(-1.809)	(-1.911)	(-1.431)	(-2.114)	(-1.924)	(-2.040)
log(EDF) × shd rate	-0.049***	-0.079***	-0.091***	-0.107**	-0.125***	-0.153***	-0.144***	-0.157**
	(-2.725)	(-3.140)	(-2.889)	(-2.454)	(-2.682)	(-2.640)	(-2.665)	(-2.386)
log(EDF) × secur. rest. × shd rate	0.005	0.011***	0.011***	0.011***	0.011**	0.019***	0.019**	0.019***
	(1.576)	(2.750)	(2.673)	(2.641)	(2.546)	(2.648)	(2.586)	(2.641)
Num. of observ.	9431	6577	6481	6422	5270	3213	3185	3164
R-sq. adj.	0.78	0.71	0.68	0.64	0.78	0.69	0.68	0.65
RMSE	0.51	0.60	0.63	0.67	0.48	0.61	0.62	0.64
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A5: Regressions for ov. cap. str.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF, pct)	0.111	0.180	0.263**	0.255*	0.241	0.315	0.298	0.292
	(1.198)	(1.520)	(1.997)	(1.701)	(1.345)	(1.392)	(1.619)	(1.369)
log(EDF, pct) × ov. cap. str.	-0.007	-0.014**	-0.013**	-0.013**	-0.013*	-0.021**	-0.021**	-0.021**
	(-1.473)	(-2.504)	(-2.396)	(-2.436)	(-1.948)	(-2.276)	(-2.289)	(-2.297)
log(EDF, pct) × shd rate, pct	-0.046*	-0.045	-0.035	-0.045	-0.077	-0.077	-0.044	-0.063
	(-1.797)	(-1.247)	(-0.893)	(-0.940)	(-1.380)	(-1.055)	(-0.716)	(-0.852)
log(EDF, pct) × ov. cap. str. × shd rate, pct	-0.001	-0.003	-0.003	-0.003	0.001	-0.003	-0.003	-0.003
	(-0.355)	(-1.364)	(-1.040)	(-1.190)	(0.299)	(-0.809)	(-0.729)	(-0.732)
Num. of observ.	5492	3763	3732	3679	2927	1735	1716	1701
R-sq. adj.	0.79	0.70	0.64	0.57	0.77	0.58	0.57	0.50
RMSE	0.49	0.61	0.66	0.73	0.52	0.74	0.76	0.81
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A6: Regressions for Basel III implementation

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.111	0.191*	0.231*	0.257	0.276	0.331	0.280*	0.291
	(1.334)	(1.744)	(1.843)	(1.557)	(1.584)	(1.648)	(1.734)	(1.420)
log(EDF) × BIII reg.	0.065	0.115	0.338**	0.344*	-0.171	-0.384	-0.374	-0.406
	(0.523)	(0.843)	(2.105)	(1.826)	(-0.568)	(-0.999)	(-1.001)	(-1.010)
log(EDF) × shd rate	-0.050***	-0.077***	-0.080**	-0.098**	-0.103**	-0.118**	-0.100**	-0.121**
	(-2.631)	(-2.986)	(-2.484)	(-2.057)	(-2.227)	(-2.199)	(-2.363)	(-2.179)
log(EDF) × BIII reg. × shd rate	0.052	0.106	0.267**	0.272**	-0.001	-0.041	-0.047	-0.059
	(0.730)	(1.069)	(2.394)	(2.041)	(-0.005)	(-0.182)	(-0.219)	(-0.252)
Num. of observ.	8244	5648	5600	5543	4811	2868	2870	2848
R-sq. adj.	0.78	0.70	0.67	0.63	0.77	0.66	0.66	0.63
RMSE	0.50	0.60	0.62	0.66	0.49	0.62	0.62	0.65
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A7: Regressions for bank accnt

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.170*	0.233*	0.274**	0.323*	0.431**	0.475*	0.420*	0.443*
	(1.818)	(1.931)	(1.994)	(1.826)	(2.204)	(1.906)	(1.916)	(1.657)
log(EDF) × bank accnt	-0.028	-0.035*	-0.024	-0.026	-0.055**	-0.055*	-0.049	-0.052
	(-1.597)	(-1.676)	(-1.105)	(-1.186)	(-2.085)	(-1.682)	(-1.507)	(-1.570)
log(EDF) × shd rate	-0.058**	-0.084***	-0.098***	-0.113**	-0.153***	-0.167**	-0.154***	-0.178**
	(-2.544)	(-2.675)	(-2.667)	(-2.328)	(-3.039)	(-2.592)	(-2.679)	(-2.459)
log(EDF) × bank accnt × shd rate	0.005	0.009	0.008	0.009	0.015**	0.015*	0.014*	0.017**
	(1.139)	(1.478)	(1.428)	(1.475)	(2.227)	(1.840)	(1.738)	(2.023)
Num. of observ.	9580	6659	6567	6506	5379	3272	3244	3225
R-sq. adj.	0.78	0.71	0.68	0.64	0.78	0.69	0.68	0.65
RMSE	0.51	0.59	0.63	0.67	0.48	0.61	0.62	0.64
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A8: Regressions insol. pwr power vs stat. trnsp

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.332**	0.372**	0.343*	0.426*	0.556**	0.449+	0.431*	0.415
	(2.436)	(2.097)	(1.774)	(1.898)	(2.378)	(1.616)	(1.723)	(1.389)
log(EDF) × insol. pwr	-0.054***	-0.072***	-0.067**	-0.059**	-0.056*	-0.079**	-0.071*	-0.071*
	(-2.710)	(-2.712)	(-2.357)	(-2.121)	(-1.834)	(-1.982)	(-1.748)	(-1.800)
log(EDF) × stat. trnsp	-0.032	-0.030	-0.011	-0.018	-0.042	-0.010	-0.010	-0.008
	(-1.552)	(-1.176)	(-0.438)	(-0.677)	(-1.446)	(-0.310)	(-0.338)	(-0.252)
log(EDF) × shd rate	-0.099***	-0.115***	-0.116**	-0.137**	-0.190***	-0.173**	-0.169**	-0.183**
	(-3.170)	(-2.743)	(-2.427)	(-2.433)	(-3.256)	(-2.455)	(-2.600)	(-2.322)
log(EDF) × insol. pwr × shd rate	0.012**	0.019***	0.019**	0.017**	0.016**	0.019*	0.019*	0.019*
	(2.310)	(2.607)	(2.521)	(2.295)	(1.982)	(1.748)	(1.678)	(1.747)
log(EDF) × stat. trnsp × shd rate	0.007*	0.006	0.004	0.005	0.012*	0.006	0.006	0.007
	(1.740)	(1.203)	(0.771)	(0.975)	(1.830)	(0.849)	(0.965)	(1.020)
Num. of observ.	9053	6266	6168	6102	5019	3015	2990	2965
R-sq. adj.	0.77	0.70	0.66	0.62	0.78	0.67	0.66	0.64
RMSE	0.51	0.61	0.64	0.69	0.48	0.62	0.63	0.65
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table A9: Regressions insol. pwr power vs accnt pract.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.142*	0.211**	0.278**	0.330**	0.341**	0.442**	0.416**	0.419*
	(1.770)	(2.040)	(2.169)	(2.133)	(1.986)	(2.144)	(2.187)	(1.869)
log(EDF) × insol. pwr	-0.062***	-0.073**	-0.066**	-0.060**	-0.054**	-0.066**	-0.060**	-0.058**
	(-2.846)	(-2.606)	(-2.339)	(-2.060)	(-1.983)	(-2.333)	(-2.129)	(-2.095)
log(EDF) × accnt pract.	0.012	-0.001	-0.007	-0.008	-0.019	-0.069**	-0.073**	-0.070**
	(0.506)	(-0.031)	(-0.234)	(-0.269)	(-0.619)	(-1.988)	(-2.173)	(-2.012)
log(EDF) × shd rate	-0.057***	-0.088***	-0.103***	-0.121***	-0.152***	-0.178***	-0.167***	-0.184***
	(-2.972)	(-3.268)	(-2.884)	(-2.802)	(-3.358)	(-3.060)	(-3.038)	(-2.846)
log(EDF) × insol. pwr × shd rate	0.014**	0.020***	0.019**	0.017**	0.014*	0.016*	0.016*	0.015*
	(2.253)	(2.611)	(2.511)	(2.186)	(1.751)	(1.717)	(1.745)	(1.670)
log(EDF) × accnt pract. × shd rate	-0.003	0.003	0.004	0.004	0.016**	0.029***	0.030***	0.029***
	(-0.376)	(0.340)	(0.457)	(0.493)	(2.136)	(3.008)	(2.864)	(2.829)
Num. of observ.	8453	5798	5700	5635	4621	2695	2680	2653
R-sq. adj.	0.76	0.68	0.63	0.57	0.76	0.64	0.63	0.60
RMSE	0.52	0.63	0.67	0.72	0.50	0.65	0.65	0.68
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects.
Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table A10: Regressions for prompt corrective power vs Basel III rg

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.215**	0.341***	0.385***	0.431***	0.443**	0.565***	0.526***	0.517***
	(2.450)	(3.232)	(3.311)	(2.876)	(2.601)	(3.080)	(3.141)	(2.640)
log(EDF) × ppt cor. pwr	-0.013**	-0.021***	-0.019**	-0.019**	-0.021***	-0.029***	-0.028**	-0.026**
	(-2.278)	(-2.747)	(-2.464)	(-2.449)	(-2.746)	(-2.656)	(-2.590)	(-2.435)
log(EDF) × Basel III rg	0.171	0.081	0.428	0.409	0.027	-0.378	-0.189	-0.546
	(1.058)	(0.308)	(1.184)	(1.151)	(0.065)	(-0.447)	(-0.239)	(-0.641)
log(EDF) × shd rate	-0.071***	-0.112***	-0.121***	-0.141***	-0.141***	-0.176***	-0.163***	-0.176***
	(-3.258)	(-4.200)	(-3.712)	(-3.273)	(-3.209)	(-3.645)	(-3.752)	(-3.445)
log(EDF) × ppt cor. pwr × shd rate	0.003**	0.005***	0.005**	0.005**	0.004*	0.006*	0.006*	0.006+
	(2.072)	(2.641)	(2.502)	(2.352)	(1.780)	(1.731)	(1.934)	(1.655)
log(EDF) × Basel III rg × shd rate	0.113	0.087	0.347+	0.338+	0.116	-0.014	0.063	-0.110
	(1.249)	(0.603)	(1.635)	(1.616)	(0.541)	(-0.036)	(0.171)	(-0.272)
Num. of observ.	7024	4728	4666	4606	3926	2268	2257	2234
R-sq. adj.	0.77	0.67	0.63	0.57	0.76	0.62	0.62	0.59
RMSE	0.51	0.63	0.67	0.72	0.49	0.65	0.65	0.68
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects.
Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table A11: Regressions insol. pwr power vs Basel III rg

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.221**	0.316***	0.326***	0.386**	0.399**	0.507**	0.447***	0.455**
	(2.510)	(2.813)	(2.693)	(2.478)	(2.302)	(2.617)	(2.628)	(2.263)
log(EDF) × insol. pwr	-0.061***	-0.074***	-0.071**	-0.065**	-0.069**	-0.092**	-0.084**	-0.084**
	(-2.977)	(-2.611)	(-2.431)	(-2.265)	(-2.182)	(-2.126)	(-1.988)	(-1.998)
log(EDF) × Basel III rg	0.153	0.128	0.533*	0.477	-0.091	-0.566	-0.389	-0.714
	(1.026)	(0.533)	(1.679)	(1.462)	(-0.229)	(-0.737)	(-0.535)	(-0.935)
log(EDF) × shd rate	-0.073***	-0.111***	-0.110***	-0.135***	-0.131***	-0.162***	-0.144***	-0.162***
	(-3.341)	(-3.930)	(-3.247)	(-3.017)	(-2.963)	(-3.154)	(-3.236)	(-3.059)
log(EDF) × insol. pwr × shd rate	0.014**	0.022**	0.023***	0.020**	0.015	0.021	0.021	0.021
	(2.235)	(2.576)	(2.628)	(2.378)	(1.569)	(1.598)	(1.602)	(1.583)
log(EDF) × Basel III rg × shd rate	0.103	0.111	0.410**	0.375*	0.064	-0.085	-0.019	-0.174
	(1.270)	(0.835)	(2.134)	(1.888)	(0.316)	(-0.230)	(-0.053)	(-0.469)
Num. of observ.	7372	4921	4858	4798	4266	2453	2441	2416
R-sq. adj.	0.77	0.67	0.63	0.57	0.76	0.63	0.63	0.59
RMSE	0.51	0.63	0.66	0.71	0.50	0.65	0.65	0.68
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table A12: Regressions for insolvency power

	Global sample			
	(1)	(2)	(3)	(4)
log(EDF)	1.862***	1.545**	2.444***	2.271
	(3.221)	(2.553)	(2.619)	(1.421)
$\overline{insol.\ pwr}$	1.832***	1.071	1.442	2.588*
	(3.531)	(1.409)	(1.490)	(1.856)
log(EDF) × $\overline{insol.\ pwr}$	-0.126	-0.331	-1.100*	-0.377
	(-0.286)	(-0.784)	(-1.726)	(-0.356)
log(EDF) × shd rate	-0.170	-0.024	0.173	-0.110
	(-0.603)	(-0.085)	(0.409)	(-0.207)
$\overline{insol.\ pwr}$ × shd rate	-0.267*	-0.078	-0.272	-0.423
	(-1.673)	(-0.473)	(-0.950)	(-1.347)
log(EDF) × $\overline{insol.\ pwr}$ × shd rate	0.142	0.142	0.177	0.159
	(0.757)	(0.757)	(0.680)	(0.488)
Num. of observ.	2231	2220	1689	1205
R-sq. adj.	0.06	0.17	0.20	0.31
RMSE	11.89	11.17	11.20	10.52
Borr. country FE	N	Y	N	Y
Borr. industry FE	N	Y	Y	N
Time FE (TFE)	Y	Y	N	N
Borr. country TFE	N	N	Y	N
Borr. industry TFE	N	N	N	Y

t statistics in parentheses
Note. Errors clustered by month.
$^{+}$ $p < 0.11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Select SRM regressions for the 1995-2008 period

In the main text, we cut the sample at 2014 because of fast-changing SRM characteristics, in particular for European banks, which account for about 40 percent of sample observations. But in this appendix, we cut the sample at 2008 a few reasons. First, we show that the findings are not solely attributable to significant changes in SRM characteristics in response to the GFC and the European sovereign and banking crises (see figure 3). Second, we show that the results are not driven by unconventional monetary policies with the federal funds rate was stuck at the zero lower bound since December 2008 (see figure 2). (As such, the federal funds rate showing no material variation over the zero lower period does not pose identification challenges because we identify the effects of interest through the double and triple interaction terms, $log(EDF_{j,b,t}) \times R_t$ and $log(EDF_{j,b,t}) \times SRM_{l,t} \times R_t$, where EDF and SRM show plenty of variation.) Third, we check whether the results for prompt corrective power are not solely driven by the 4th survey in Barth, Caprio, and Levine (2013).

We reestimate the regressions for SRM characteristics that have statistically significant mitigating or amplifying effects on risk-taking in response to lower U.S. policy rates for a pre-GFC period from 1995 to 2008. We show the new estimation results below in tables A13 to A17 and highlight those in table 4 in the main text.

Table A13: Regressions for base line

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.237	0.332	0.556**	0.553*	0.446	0.608**	0.636	0.633**
	(1.269)	(1.543)	(2.121)	(1.941)	(1.619)	(2.240)	(1.615)	(2.110)
log(EDF) × fnd rate	-0.065	-0.101*	-0.157**	-0.155**	-0.145**	-0.186**	-0.212*	-0.210**
	(-1.436)	(-1.919)	(-2.472)	(-2.198)	(-2.010)	(-2.421)	(-1.748)	(-2.381)
Num. of observ.	5947	4110	4053	4021	3472	2176	2168	2153
R-sq. adj.	0.75	0.69	0.64	0.61	0.76	0.68	0.67	0.65
RMSE	0.52	0.61	0.64	0.67	0.46	0.57	0.58	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effect. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A14: Regressions for ppt cor. pwr

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.276	0.415**	0.639***	0.643**	0.549**	0.739***	0.766***	0.769***
	(1.531)	(2.003)	(2.649)	(2.509)	(2.113)	(2.952)	(2.929)	(2.756)
log(EDF) × ppt cor. pwr	-0.008	-0.019***	-0.013**	-0.013**	-0.025***	-0.032***	-0.032***	-0.032***
	(-0.974)	(-4.326)	(-2.298)	(-2.315)	(-2.773)	(-6.266)	(-5.965)	(-6.045)
log(EDF) × fnd rate	-0.072	-0.119**	-0.176***	-0.175***	-0.168**	-0.216***	-0.242***	-0.242***
	(-1.600)	(-2.294)	(-2.903)	(-2.708)	(-2.390)	(-2.915)	(-3.072)	(-2.829)
log(EDF) × ppt cor. pwr × fnd rate	0.002	0.005***	0.004**	0.004**	0.006***	0.008***	0.008***	0.008***
	(0.852)	(3.409)	(2.475)	(2.462)	(2.630)	(3.951)	(3.905)	(3.933)
Num. of observ.	5637	3926	3871	3842	3171	2002	1993	1981
R-sq. adj.	0.75	0.69	0.65	0.61	0.77	0.69	0.68	0.66
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.57	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A15: Regressions for insol. pwr

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.261	0.414**	0.576**	0.573**	0.501*	0.694**	0.720**	0.721**
	(1.437)	(1.987)	(2.200)	(2.068)	(1.875)	(2.555)	(2.597)	(2.426)
log(EDF) × insol. pwr	-0.015	-0.051**	-0.013	-0.012	-0.044***	-0.068***	-0.068***	-0.069***
	(-0.733)	(-2.167)	(-0.616)	(-0.558)	(-2.691)	(-3.581)	(-3.258)	(-3.504)
log(EDF) × fnd rate	-0.069	-0.122**	-0.165**	-0.163**	-0.161**	-0.208***	-0.233***	-0.233***
	(-1.547)	(-2.344)	(-2.590)	(-2.393)	(-2.306)	(-2.737)	(-2.975)	(-2.706)
log(EDF) × insol. pwr × fnd rate	0.003	0.013**	0.006	0.006	0.013**	0.017**	0.018*	0.018**
	(0.509)	(2.282)	(1.024)	(0.982)	(2.155)	(1.994)	(1.934)	(2.016)
Num. of observ.	5869	4071	4016	3984	3396	2139	2133	2118
R-sq. adj.	0.75	0.69	0.64	0.61	0.76	0.68	0.67	0.65
RMSE	0.52	0.61	0.64	0.67	0.46	0.57	0.57	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A16: Regressions for stat. trnsp

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.402	0.330	0.618	0.648	0.818***	1.039***	1.062***	1.078***
	(1.563)	(0.906)	(1.614)	(1.625)	(2.633)	(2.786)	(2.723)	(2.689)
log(EDF) × stat. trnsp	-0.027	0.007	-0.001	-0.007	-0.061*	-0.070	-0.069	-0.072
	(-0.658)	(0.116)	(-0.024)	(-0.117)	(-1.972)	(-1.403)	(-1.340)	(-1.419)
log(EDF) × fnd rate	-0.100*	-0.097	-0.169*	-0.176*	-0.233***	-0.290***	-0.319***	-0.325***
	(-1.702)	(-1.226)	(-1.969)	(-1.956)	(-2.921)	(-3.011)	(-3.191)	(-3.112)
log(EDF) × stat. trnsp × fnd rate	0.006	-0.002	0.000	0.002	0.015**	0.017	0.018	0.019*
	(0.711)	(-0.184)	(0.023)	(0.143)	(2.046)	(1.588)	(1.623)	(1.767)
Num. of observ.	5903	4092	4035	4003	3428	2157	2149	2134
R-sq. adj.	0.75	0.69	0.64	0.61	0.76	0.67	0.67	0.65
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.58	0.60
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A17: Regressions for accnt pract.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.300	0.461*	0.608**	0.618**	0.614*	0.816**	0.830**	0.850**
	(1.352)	(1.916)	(2.187)	(2.084)	(1.915)	(2.468)	(2.550)	(2.431)
log(EDF) × accnt pract.	0.017	0.026	0.043	0.043	-0.105	-0.086	-0.093	-0.091
	(0.256)	(0.299)	(0.486)	(0.489)	(-1.648)	(-1.157)	(-1.238)	(-1.204)
log(EDF) × fnd rate	-0.089	-0.148**	-0.189***	-0.191**	-0.218***	-0.270***	-0.295***	-0.300***
	(-1.591)	(-2.457)	(-2.754)	(-2.590)	(-2.767)	(-3.121)	(-3.509)	(-3.296)
log(EDF) × accnt pract. × fnd rate	-0.001	-0.001	-0.004	-0.005	0.040***	0.034**	0.037**	0.036**
	(-0.071)	(-0.056)	(-0.231)	(-0.236)	(3.002)	(2.032)	(2.125)	(2.099)
Num. of observ.	5267	3608	3549	3518	3006	1834	1833	1817
R-sq. adj.	0.73	0.64	0.58	0.54	0.73	0.62	0.62	0.59
RMSE	0.53	0.64	0.69	0.73	0.48	0.61	0.60	0.63
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Select prompt corrective powers regressions for the 1995-2008 period

In this section, we present the estimation results for finely-defined prompt corrective powers for the 1995-2008 sample.

Table A18: Regressions for earl. interv.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.281	0.404*	0.632***	0.633**	0.563**	0.738***	0.768***	0.772***
	(1.606)	(1.972)	(2.639)	(2.488)	(2.240)	(2.946)	(2.950)	(2.765)
log(EDF) × earl. interv.	-0.032	-0.074*	-0.050	-0.050	-0.148***	-0.165***	-0.167***	-0.169***
	(-0.653)	(-1.691)	(-1.065)	(-1.065)	(-2.952)	(-3.788)	(-3.824)	(-3.956)
log(EDF) × shd rate	-0.073*	-0.117**	-0.175***	-0.174***	-0.173**	-0.216***	-0.243***	-0.243***
	(-1.677)	(-2.283)	(-2.903)	(-2.696)	(-2.547)	(-2.942)	(-3.137)	(-2.877)
log(EDF) × earl. interv. × shd rate	0.007	0.019*	0.016	0.016	0.039***	0.040***	0.042***	0.043***
	(0.576)	(1.788)	(1.436)	(1.441)	(2.789)	(2.745)	(2.836)	(2.940)
Num. of observ.	5891	4081	4026	3994	3416	2146	2140	2125
R-sq. adj.	0.75	0.68	0.64	0.61	0.76	0.67	0.67	0.65
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.58	0.60
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A19: Regressions for cease order

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.265	0.366*	0.619**	0.623**	0.522*	0.747***	0.764***	0.769***
	(1.389)	(1.665)	(2.484)	(2.352)	(1.917)	(2.936)	(2.946)	(2.753)
log(EDF) × cease order	-0.072	-0.074	-0.117***	-0.121***	-0.119**	-0.207***	-0.200***	-0.203***
	(-1.192)	(-1.427)	(-2.752)	(-2.921)	(-1.993)	(-4.032)	(-4.145)	(-4.284)
log(EDF) × shd rate	-0.071	-0.110**	-0.172***	-0.171***	-0.164**	-0.222***	-0.246***	-0.246***
	(-1.531)	(-2.057)	(-2.847)	(-2.650)	(-2.288)	(-3.006)	(-3.227)	(-2.955)
log(EDF) × cease order × shd rate	0.016	0.019	0.030***	0.031***	0.031*	0.056***	0.055***	0.056***
	(1.187)	(1.495)	(2.647)	(2.787)	(1.958)	(3.423)	(3.413)	(3.489)
Num. of observ.	5913	4090	4033	4001	3438	2156	2148	2133
R-sq. adj.	0.75	0.69	0.65	0.61	0.76	0.68	0.68	0.66
RMSE	0.52	0.61	0.64	0.67	0.46	0.57	0.57	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A20: Regressions for susp. divid.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.311*	0.487**	0.700***	0.697**	0.668***	0.848***	0.880***	0.884***
	(1.667)	(2.338)	(2.767)	(2.603)	(2.761)	(3.423)	(3.436)	(3.237)
log(EDF) × susp. divid.	-0.078	-0.172**	-0.163*	-0.160*	-0.244***	-0.270***	-0.277***	-0.280***
	(-1.198)	(-2.196)	(-1.949)	(-1.893)	(-3.787)	(-3.217)	(-3.127)	(-3.253)
log(EDF) × shd rate	-0.086*	-0.137**	-0.192***	-0.190***	-0.199***	-0.237***	-0.266***	-0.266***
	(-1.845)	(-2.591)	(-3.055)	(-2.839)	(-3.096)	(-3.352)	(-3.586)	(-3.301)
log(EDF) × susp. divid. × shd rate	0.023	0.040**	0.040*	0.039*	0.060***	0.056***	0.061***	0.062***
	(1.406)	(2.089)	(1.938)	(1.894)	(3.455)	(2.739)	(2.814)	(2.896)
Num. of observ.	5874	4056	4001	3970	3408	2131	2122	2108
R-sq. adj.	0.75	0.69	0.64	0.61	0.76	0.68	0.67	0.65
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.57	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A21: Regressions for susp. bonus.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.275	0.354	0.565**	0.566**	0.553**	0.747***	0.766***	0.772***
	(1.463)	(1.559)	(2.118)	(2.000)	(2.066)	(2.870)	(2.874)	(2.705)
log(EDF) × susp. bonus.	-0.049	-0.031	-0.017	-0.018	-0.148**	-0.183***	-0.180**	-0.184***
	(-0.896)	(-0.444)	(-0.225)	(-0.241)	(-2.469)	(-2.682)	(-2.587)	(-2.667)
log(EDF) × shd rate	-0.073	-0.108*	-0.162**	-0.161**	-0.173**	-0.223***	-0.247***	-0.247***
	(-1.567)	(-1.912)	(-2.476)	(-2.306)	(-2.454)	(-2.987)	(-3.202)	(-2.949)
log(EDF) × susp. bonus. × shd rate	0.010	0.009	0.009	0.009	0.039***	0.049***	0.050***	0.051***
	(0.737)	(0.562)	(0.509)	(0.526)	(2.614)	(2.811)	(2.707)	(2.792)
Num. of observ.	5874	4056	4001	3970	3408	2131	2122	2108
R-sq. adj.	0.75	0.69	0.64	0.61	0.76	0.68	0.68	0.65
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.57	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A22: Regressions for susp. fees

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.303	0.396*	0.628**	0.630**	0.605**	0.787***	0.813***	0.819***
	(1.653)	(1.780)	(2.509)	(2.362)	(2.429)	(3.240)	(3.258)	(3.032)
log(EDF) × susp. fees	-0.065	-0.040	-0.020	-0.021	-0.180**	-0.166**	-0.165**	-0.168**
	(-1.156)	(-0.542)	(-0.254)	(-0.267)	(-2.559)	(-2.105)	(-2.088)	(-2.125)
log(EDF) × shd rate	-0.077*	-0.114**	-0.173***	-0.172**	-0.180***	-0.226***	-0.252***	-0.252***
	(-1.667)	(-2.048)	(-2.745)	(-2.549)	(-2.620)	(-3.098)	(-3.322)	(-3.038)
log(EDF) × susp. fees × shd rate	0.011	0.008	0.006	0.007	0.040**	0.038*	0.038*	0.039*
	(0.823)	(0.456)	(0.348)	(0.366)	(2.323)	(1.770)	(1.757)	(1.803)
Num. of observ.	5748	4009	3950	3920	3273	2076	2066	2053
R-sq. adj.	0.75	0.69	0.65	0.61	0.77	0.68	0.68	0.66
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.57	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
* $p < .1$, ** $p < .05$, *** $p < .01$

"Horse race" regressions for the 1995-2008

In this section, we present the estimation results for "horse race" regressions for the 1995-2008 sample where we include two characteristics at a time to identify the characteristics that have most robust or complementary effects. As in the main text, these characteristics are two supervisory powers—prompt corrective power and declaring insolvency power—and two transparency characteristics—financial statement transparency and accounting practices.

Table A23: Regressions ppt cor. pwr power vs insol. pwr

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.283+	0.443**	0.616**	0.618**	0.526**	0.728***	0.752***	0.758***
	(1.611)	(2.248)	(2.545)	(2.406)	(2.073)	(2.890)	(2.874)	(2.705)
log(EDF) × ppt cor. pwr	-0.007	-0.014**	-0.022***	-0.023***	-0.031***	-0.035***	-0.036***	-0.035***
	(-0.813)	(-2.325)	(-3.229)	(-3.382)	(-3.338)	(-2.690)	(-2.802)	(-2.771)
log(EDF) × insol. pwr	-0.003	-0.023	0.038	0.040+	0.026**	0.014	0.017	0.014
	(-0.160)	(-0.703)	(1.467)	(1.613)	(2.286)	(0.303)	(0.353)	(0.299)
log(EDF) × shd rate	-0.074*	-0.127**	-0.172***	-0.171***	-0.166**	-0.216***	-0.241***	-0.242***
	(-1.681)	(-2.563)	(-2.889)	(-2.684)	(-2.428)	(-2.972)	(-3.158)	(-2.900)
log(EDF) × ppt cor. pwr × shd rate	0.001	0.003**	0.005***	0.005***	0.007***	0.008**	0.008***	0.008**
	(0.676)	(2.127)	(3.049)	(3.135)	(2.867)	(2.414)	(2.643)	(2.551)
log(EDF) × insol. pwr × shd rate	0.001	0.007	-0.007	-0.007	-0.003	-0.000	-0.001	0.000
	(0.253)	(1.006)	(-0.981)	(-1.054)	(-0.664)	(-0.018)	(-0.071)	(0.016)
Num. of observ.	5607	3914	3859	3830	3144	1992	1983	1971
R-sq. adj.	0.75	0.69	0.65	0.61	0.77	0.69	0.68	0.66
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.57	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table A24: Regressions ppt cor. pwr power vs stat. trnsp

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.401	0.358	0.618	0.651+	0.871***	1.135***	1.145***	1.171***
	(1.499)	(0.983)	(1.606)	(1.621)	(2.811)	(3.362)	(3.288)	(3.199)
log(EDF) × ppt cor. pwr	-0.008	-0.019***	-0.013**	-0.013**	-0.025***	-0.033***	-0.034***	-0.034***
	(-1.008)	(-3.935)	(-2.184)	(-2.227)	(-2.976)	(-6.015)	(-5.828)	(-6.019)
log(EDF) × stat. trnsp	-0.025	0.011	0.004	-0.002	-0.063*	-0.074*	-0.071	-0.075*
	(-0.566)	(0.189)	(0.066)	(-0.030)	(-1.948)	(-1.717)	(-1.600)	(-1.688)
log(EDF) × shd rate	-0.099+	-0.106	-0.174*	-0.181*	-0.248***	-0.323***	-0.352***	-0.360***
	(-1.630)	(-1.313)	(-1.975)	(-1.964)	(-3.072)	(-3.531)	(-3.765)	(-3.612)
log(EDF) × ppt cor. pwr × shd rate	0.002	0.005***	0.004**	0.004**	0.006***	0.008***	0.009***	0.009***
	(0.882)	(3.141)	(2.331)	(2.343)	(2.835)	(3.686)	(3.735)	(3.836)
log(EDF) × stat. trnsp × shd rate	0.006	-0.003	-0.000	0.001	0.015**	0.020**	0.020**	0.022**
	(0.646)	(-0.223)	(-0.029)	(0.094)	(2.133)	(2.052)	(2.078)	(2.212)
Num. of observ.	5637	3926	3871	3842	3171	2002	1993	1981
R-sq. adj.	0.75	0.69	0.65	0.61	0.77	0.69	0.68	0.66
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.57	0.59
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table A25: Regressions ppt cor. pwr power vs accnt pract.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.330	0.520**	0.672***	0.689**	0.695**	0.915***	0.928***	0.956***
	(1.503)	(2.264)	(2.635)	(2.523)	(2.256)	(3.024)	(3.088)	(2.958)
log(EDF) × ppt cor. pwr	-0.004	-0.018***	-0.013**	-0.013**	-0.014	-0.022***	-0.022***	-0.023***
	(-0.377)	(-2.911)	(-2.010)	(-2.057)	(-1.227)	(-2.864)	(-2.953)	(-2.937)
log(EDF) × accnt pract.	0.022	0.066	0.074	0.074	-0.079	-0.049	-0.055	-0.051
	(0.273)	(0.681)	(0.775)	(0.779)	(-0.801)	(-0.494)	(-0.547)	(-0.503)
log(EDF) × shd rate	-0.093+	-0.159***	-0.202***	-0.206***	-0.237***	-0.292***	-0.317***	-0.325***
	(-1.645)	(-2.728)	(-3.110)	(-2.943)	(-3.055)	(-3.586)	(-3.979)	(-3.763)
log(EDF) × ppt cor. pwr × shd rate	-0.000	0.004**	0.003*	0.003*	0.003	0.004	0.005	0.005*
	(-0.163)	(2.190)	(1.706)	(1.714)	(0.847)	(1.478)	(1.611)	(1.664)
log(EDF) × accnt pract. × shd rate	0.002	-0.010	-0.011	-0.011	0.037*	0.026	0.030	0.028
	(0.108)	(-0.445)	(-0.509)	(-0.516)	(1.661)	(1.221)	(1.286)	(1.224)
Num. of observ.	4957	3424	3367	3338	2705	1660	1658	1644
R-sq. adj.	0.73	0.64	0.58	0.53	0.74	0.63	0.63	0.60
RMSE	0.54	0.65	0.70	0.74	0.47	0.61	0.60	0.63
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table A26: Regressions insol. pwr power vs stat. trnsp

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.426*	0.437	0.670*	0.701*	0.870***	1.163***	1.183***	1.208***
	(1.689)	(1.215)	(1.727)	(1.742)	(2.980)	(3.175)	(3.113)	(3.071)
log(EDF) × insol. pwr	-0.016	-0.054**	-0.015	-0.014	-0.045*	-0.074***	-0.075***	-0.077***
	(-0.822)	(-2.209)	(-0.729)	(-0.700)	(-1.890)	(-4.432)	(-3.837)	(-4.227)
log(EDF) × stat. trnsp	-0.026	0.003	-0.007	-0.012	-0.060*	-0.076	-0.074	-0.077
	(-0.632)	(0.054)	(-0.112)	(-0.209)	(-1.846)	(-1.472)	(-1.405)	(-1.474)
log(EDF) × shd rate	-0.105*	-0.125	-0.187**	-0.194**	-0.251***	-0.326***	-0.356***	-0.364***
	(-1.753)	(-1.558)	(-2.079)	(-2.070)	(-3.289)	(-3.406)	(-3.670)	(-3.568)
log(EDF) × insol. pwr × shd rate	0.003	0.014**	0.007	0.006	0.014**	0.020**	0.020*	0.022**
	(0.579)	(2.180)	(1.063)	(1.063)	(2.005)	(1.992)	(1.953)	(2.034)
log(EDF) × stat. trnsp × shd rate	0.006	-0.001	0.002	0.003	0.015**	0.019*	0.020*	0.021*
	(0.690)	(-0.073)	(0.147)	(0.271)	(2.036)	(1.707)	(1.756)	(1.884)
Num. of observ.	5824	4053	3998	3966	3351	2120	2114	2099
R-sq. adj.	0.75	0.69	0.64	0.61	0.76	0.67	0.67	0.65
RMSE	0.52	0.61	0.65	0.68	0.46	0.57	0.58	0.60
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$

Table A27: Regressions insol. pwr power vs accnt pract.

	Global sample				non-U.S. sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(EDF)	0.306	0.511**	0.616**	0.626**	0.618*	0.856**	0.865***	0.887**
	(1.385)	(2.104)	(2.209)	(2.097)	(1.955)	(2.569)	(2.654)	(2.523)
log(EDF) × insol. pwr	-0.003	-0.047*	-0.015	-0.013	-0.009	-0.044**	-0.039**	-0.041**
	(-0.144)	(-1.871)	(-0.632)	(-0.566)	(-0.485)	(-1.987)	(-2.059)	(-2.117)
log(EDF) × accnt pract.	0.014	0.060	0.063	0.062	-0.100	-0.067	-0.075	-0.071
	(0.199)	(0.590)	(0.652)	(0.649)	(-1.394)	(-0.734)	(-0.831)	(-0.784)
log(EDF) × shd rate	-0.087	-0.160***	-0.192***	-0.194**	-0.218***	-0.278***	-0.301***	-0.308***
	(-1.553)	(-2.632)	(-2.792)	(-2.611)	(-2.809)	(-3.182)	(-3.578)	(-3.338)
log(EDF) × insol. pwr × shd rate	-0.002	0.013*	0.006	0.006	0.001	0.010	0.009	0.010
	(-0.339)	(1.745)	(0.913)	(0.849)	(0.179)	(0.931)	(0.876)	(0.929)
log(EDF) × accnt pract. × shd rate	0.002	-0.011	-0.011	-0.011	0.039**	0.029	0.032	0.031
	(0.111)	(-0.473)	(-0.493)	(-0.489)	(2.520)	(1.452)	(1.570)	(1.512)
Num. of observ.	5189	3569	3512	3480	2930	1797	1798	1781
R-sq. adj.	0.73	0.64	0.58	0.53	0.73	0.62	0.62	0.59
RMSE	0.53	0.64	0.69	0.73	0.48	0.61	0.61	0.63
Bank country TFE	Y	N	N	N	Y	N	N	N
Borrower country TFE	Y	Y	N	N	Y	Y	N	N
Borrower industry TFE	N	N	Y	N	N	N	Y	N
Bank TFE	N	Y	Y	Y	N	Y	Y	Y
Borrower TFE	N	N	N	Y	N	N	N	Y

t statistics in parentheses
Note. All regressions have individual lender and borrower fixed effects. TFE stands for time fixed effects. Errors clustered by bank and month.
$^{+}$ $p < .11$, * $p < .1$, ** $p < .05$, *** $p < .01$