Essays on the Measurement and Detection of Risk in Banks

by

Thomas M. Flanagan

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Doctoral Committee:

Professor Emeritus Charlie Brown
Associate Professor Andrey Malenko
Professor Amiyatosh Purnanandam, Chair
Professor Uday Rajan
Professor Christopher Williams

Thomas Flanagan

tflan@umich.edu

ORCID iD: 0000-0002-1039-9401

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ABSTRACT

This dissertation explores different aspects of risk measurement in banks, including the risk-adjusted returns of bank lending activities, the financial returns earned by taxpayers on bailouts, and the economic drivers behind banks' risk-hiding behavior.

In Chapter 1, I study the value of bank lending. Although a vast theoretical literature suggests that banks' screening and monitoring skill makes them special, there is limited direct evidence on the level and sources of value creation from bank lending activities. Using a novel dataset of realized syndicated loan cash-flows and a risk-adjustment methodology adapted from the private equity literature, I provide a loan-level measure of the value of bank lending activities. I show that banks, on average, earn 190 bps in risk-adjusted returns on each loan they make. Cross-sectionally, banks earn higher risk-adjusted returns when they lend to financially constrained borrowers and when they retain a higher stake in the deal. In addition to banks earning risk-adjusted income, I show that borrowers are also better off and capture some of the surplus through higher stock market valuations. Overall, my results show direct evidence of banks' critical role in mitigating borrowers' financing frictions and provide a useful input for policies that encourage prudent lending.

In Chapter 2, I study the financial returns earned by taxpayers on the Troubled Asset Relief Program (TARP). Financial institutions received investments under TARP in a bad state of the world but repaid them in a relatively good state. I show that the recipients paid considerably lower returns to the taxpayers compared to private market securities with similar risk over the same investment horizon, resulting in a subsidy of over $50 billion. Ex-post renegotiation of contract terms contributed to the subsidy and limited the upside gains received by the taxpayers in good times. While I do not evaluate the net social benefit of

TARP, the results challenge the oft-cited narrative that taxpayers made "profits" on TARP from a purely financial perspective. These findings have important implications for the design of future bailouts and theoretical models in the area.

In Chapter 3, I study why banks hide losses. Despite plenty of anecdotal evidence of hidden losses in banks, there is no systematic study analyzing its economic drivers: we simply do not get to observe what banks are hiding. Using a regulatory change in India that forced banks to reveal their hidden losses, I show that banks with higher shareholding by passive foreign investors hide more. These effects are stronger for banks where CEOs get highly compensated for reported profits. The findings caution against using high-powered compensation contracts as a substitute for active shareholder monitoring. Instead of solving the agency problem, it can result in perverse misreporting incentives.

Overall, my dissertation demonstrates that banks can create value net of the risk they take when lending. However, government interventions and shareholder-manager conflicts can also destroy value, resulting in negative financial returns to taxpayers and hidden losses in the system.

Chapter 1: The Value of Bank Lending

1.1 Introduction

Why do banks exist? Classic theories suggest that they add value through services such as maturity and liquidity transformation, risk diversification, and screening and monitoring of their borrowers. Banks' ability to screen and monitor is considered especially important because of their role in mitigating firms' financial constraints in the real economy (Leland and Pyle, 1977; Diamond, 1984; Ramakrishnan and Thakor, 1984). To the extent that banks produce information and monitor when lending, they should create value by earning risk-adjusted income on loans compared to a public capital market. On the other hand, repeated episodes of financial crises and government bailouts raise valid concerns about excessive risk-taking by banks: Are they truly providing valuable services, or are they simply taking risk and exploiting government guarantees they enjoy through regulations (Atkeson et al., 2019)? Understanding the level and cross-sectional drivers of value creation across loans is especially important for any policies aimed at encouraging prudent lending. To which borrowers do banks provide the most screening and monitoring? Despite the centrality of these arguments to the theoretical and empirical literature in banking, there is little empirical evidence quantifying the value of bank lending.

In this paper, I provide one of the first comprehensive and direct pieces of evidence on the value of bank lending by estimating the risk-adjusted returns of syndicated bank loans in the United States over the last 30 years. Motivated by theoretical papers that quantify the value added by bank activities over public market-based outcomes (Wang, 2003), I define the value of bank lending in a precise manner: the risk-adjusted income banks earn on loans net of what a public market benchmark of identical risk would make. This definition measures the present discounted value of loan cash-flows paid to the bank and directly speaks to whether bank loans have positive value from banks' information production and monitoring abilities or negative value from distorted incentives that come with government guarantees or shareholder-manager conflicts. Although this measure does not account for how the bank distributes this value among different stakeholders, including managers and shareholders, or what resources its employees used to produce this output, I investigate these as well.

The main contribution of this paper is to quantify the value of bank lending, to explore cross-sectional drivers of the value creation in lending in line with the theories, and to examine how this risk-adjusted income is distributed among different stakeholders. Estimating the value of bank loans is difficult for two main reasons: (i) there is limited data on realized cash-flows of bank loans, and (ii) these private cash-flows do not trade in markets. I overcome these challenges by first constructing a novel dataset of realized cash-flows of all syndicated term loans to public firms in Dealscan, including the exact timing of prepayments from web-scraped SEC filings and detailed information on defaults and restructurings. Second, I adapt a recently developed methodology for estimating the risk-adjusted performance of private cash-flows (Gupta and Van Nieuwerburgh, 2021) to bank loans to obtain an empirical measure of loan values relative to a public market benchmark. Following this methodology, I regress the cash-flows of loans on the pay-offs of benchmarks consisting of publicly traded bonds and stocks for which I observe market prices. I extend Gupta and Van Nieuwerburgh (2021) in several ways, including developing statistical inference for the point estimates, constructing tradeable benchmark funds with cash-flows resembling amortizing term loans, and using market returns to derive prices rather than rely on an asset pricing model. The benchmark funds explain almost all the variation in loan cash-flows. Furthermore, they are reasonable at pricing "debt-like" cash-flows: the benchmark funds correctly value corporate bond cash-flows, for which I already know the price. The difference in the price of the benchmark funds and the cost of investing in loans measures the risk-adjusted return, which I annualize to directly measure the value added on $1 of bank loan per year.

Using a sample of 8,000 syndicated term loans to public firms from 1992 to 2014, I estimate banks earn an annual 190 basis points in risk-adjusted returns on their loans. The loan sample consists of $176 billion in outstanding syndicated term loans each year, translating into $3.3 billion per year in value added. Conservatively extrapolating these estimates to all outstanding commercial loans in the United States, bank lending adds $22.7 billion per year on a risk-adjusted basis. This is a conservative bound on the total value added as syndicated loans are, in general, less informatively intensive than commercial loans.

In the next section of the paper, I conduct a series of cross-sectional tests to analyze the financial frictions driving risk-adjusted returns in line with theories of financial intermediation. To examine cross-sectional variation, I form buckets of portfolios sorted on loan-level characteristics and separately estimate the risk exposures for each bucket. By definition, my risk-adjusted methodology allows me to assess the impact of cross-sectional characteristics on frictions affecting bank loan income independent of the riskiness of loans. This novel contribution to the banking literature allows researchers and policy-makers to examine the drivers of the value in bank lending by holding fixed the riskiness of cash-flows.

In the first cross-sectional test, I examine whether banks earn higher risk-adjusted returns when lending to more financially constrained borrowers, for which classic theories predict there is greater scope for banks to produce information and monitor (Leland and Pyle, 1977; Diamond, 1984; Fama, 1985; Ramakrishnan and Thakor, 1984). Similar to how mutual funds earn risk-adjusted returns by acquiring private information (Ferson, 2010; Berk and Green, 2004), banks can create value when screening and monitoring borrowers by improving expected cash-flows or lowering the required rate of return on the loan.[1] In contrast to the classic view, theories of excessive risk-taking suggest that bank shareholders make negative NPV loans that increase their option value by exploiting government guarantees (Keeley, 1990). This view predicts that banks destroy more value when lending to financially constrained borrowers, whose riskiness is less observable to markets and regulators.

To measure financial constraints, I follow the existing literature and use four simple

[1] Unlike mutual funds, however, there may be larger positive externalities from lending since monitoring alters firm behavior and screening determines which projects are funded (Manove et al., 2001).

measures: firm size, firm age, whether the firm has issued a corporate bond, and whether the borrower has a long-term credit rating (Hadlock and Pierce, 2010; Sufi, 2007; Chava and Purnanandam, 2011). I consolidate these measures by taking their first principal component as the paper's primary measure of financial constraints. Using this measure, I find that banks earn 66% higher risk-adjusted returns on loans in the top quartile of financially constrained borrowers compared with those in the bottom quartile. This finding supports the predictions of classic theories of banking: banks create more value when engaging in more intensive information production and monitoring for financially constrained borrowers.

One concern is that the association between financial constraints and risk-adjusted returns reflects differences in banks' market power rather than mitigation of financing frictions. Under competitive lending pressure, the value of bank lending activities should be larger when the bank uses more resources to provide more intense screening and monitoring because informational frictions are stronger (Schenone, 2010). To tease out these channels, I examine how risk-adjusted returns cross-sectionally vary with two measures: (i) the physical distance between the borrower and lender, and (ii) the strength of the borrower-lender relationship. When a borrower and lender are located closer together, the informational frictions are smaller, but the banks' scope for market power is larger. Similarly, relationship banking theories predict that, as banks specialize and acquire information about a particular borrower, the informational frictions decline for subsequent loans (Diamond, 1991). In contrast, another view is that relationship lenders capture value through an informational monopoly over their borrowers (Rajan, 1992; Sharpe, 1990). Supporting the competitive lending interpretation, I find that banks earn 30% lower risk-adjusted returns when physically closer to the borrower and 21 to 29% lower risk-adjusted returns when the bank has a more intense or longer lending relationship with a borrower. These findings reinforce the previous interpretation that the value of lending to financially constrained firms comes from the mitigation of financing frictions.

Although the tests above speak to the value of bank lending when the borrower's need for screening and monitoring is high, another important determinant of screening and monitoring is whether the bank is incentivized to do so. As delegated monitors, banks face agency and shareholder-regulatory conflicts that may diminish their incentives to screen and monitor borrowers. I study these incentive conflicts in the context of the fraction of the loan the bank retains on its balance sheet. Holding more capital in the loan enables banks to internalize the pay-off to monitoring and screening, whereas selling more of the loan to outside investors minimizes banks' incentives to provide these services (Leland and Pyle, 1977; Holmstrom and Tirole, 1997; Ivashina, 2009; Allen et al., 2011; Hu and Varas, 2021; Diamond et al., 2022). Consistent with these theories emphasizing skin in the game, banks with higher on-balance-sheet loan retention originate loans that earn 32% higher risk-adjusted returns: banks add more value when they retain a larger fraction of the loan. These findings support the view that keeping a stake in risky investments ensures incentive compatibility for banks, allowing them to add value by providing lending services. Overall, my results so far document that bank lending is valuable, especially when the need for monitoring is high and the incentives to monitor are strong.

Are borrowers better off when the bank adds more value? By revealed preference, borrowers will only choose a loan if it is better than their outside financing options, implying that the estimates of the value of loans held by the bank are a lower bound on the total social value shared between the banks and borrowers. To quantify the borrowers' gains, a loan should decrease borrowers' cost of capital and more so if they face severe financial constraints.[2] Supporting this prediction, I show that, upon loan announcement (James, 1987), stock and bond returns for the sample are positive and larger for more financially constrained firms. This indicates that borrowers capture some surplus through the spillover effects of loans onto stock and bond prices. I also show that more constrained borrowers have relatively cheaper loan pricing than yields of bonds just issued by the firm, consistent with the findings of Agarwal et al. (2021). Together, the findings indicate that, when a bank lends to a more constrained borrower, the value created goes up for both the lender and the borrower.

In the final part of the paper, I examine how the risk-adjusted income from bank lending

[2] In general, bank's screening and monitoring abilities can lower discount rates or improve the firms' expected cash-flows.

is distributed among bank stakeholders. Because I provide a "gross" measure of risk-adjusted returns (i.e., before payouts to any bank stakeholders), this measure does not decompose how much risk-adjusted income flows to shareholders or manager compensation. To analyze this division, I provide a back-of-the-envelope estimate of the non-interest expense ratio for commercial loans. The key challenge in constructing this estimate is that banking datasets like FRY-9C report the total non-interest expense of the bank but not the expenses attributable to commercial lending. To overcome this difficulty, I follow the hedonic regression approach of Hanson et al. (2015) to obtain an estimate of the expense ratio for a hypothetical bank whose only assets are commercial loans, which are funded using wholesale financing and equity. Using this approach, I find the average non-interest expense ratio for commercial lending is 164 bps, which consists of 109 bps of staff compensation and 55 bps of other operational expenses. Based on these estimates, shareholders receive 26 bps of the 190 bps in risk-adjusted returns.[3] Analogous to skilled fund managers in Berk and Green (2004), most of the value added goes to compensate bank staff for their labor involved in screening and monitoring, leaving a smaller magnitude of economic profits captured by shareholders. Even if shareholders do not receive much value from lending, the positive risk-adjusted returns indicate that the lending activity in itself is still 'valuable.' Banks are significantly engaged in information production and monitoring when lending to borrowers, which leads to a more efficient economic allocation, as demonstrated in Berk and Green (2004), even though shareholders capture no economic profits in equilibrium. Together, the results are consistent with employees being paid competitive salaries to alleviate firms' financing frictions as in the model of Philippon (2010).

The risk-adjustment methodology is robust to many alternative specifications and additional tests. I perform the Gagliardini et al. (2019) test for omitted factors using the residuals of the loan cash-flows and cannot reject the null hypothesis that the factor structure of loan cash-flows is spanned by the public market benchmarks. Both the level and cross-sectional results in the paper are similar when I relax assumptions about loan cash-flows and implement alternative estimation procedures, including elastic net and loan-level rather than

[3]The payout to shareholders calculation assumes that bank debt is fairly priced.

portfolio-level estimation. Finally, I also show that the results are robust to including several loan-level controls in my analysis.

The paper has important implications for banking regulation. First, my paper informs the policy debate on the optimal regulation of the scope of banking activities. My paper shows that the lending side of commercial banks is valuable independent of the bank's other operations. More research, however, is needed on whether government safety nets encourage value destruction in non-traditional bank assets, such as off-balance sheet items and trading divisions. Second, my paper highlights an inherent trade-off in macroprudential policies. Smaller firms are, of course, riskier, but on a risk-adjusted basis, the value of these loans is larger. Recent empirical studies (e.g., Cortés et al. (2020)) confirm that loans to smaller firms are taxed more by macroprudential policies. The positive risk-adjusted returns, however, indicate that bank lending services are also good from a macroprudential perspective. They potentially reduce risk in the economy that would otherwise occur through financing in public capital markets. Furthermore, the findings conflict with narratives from regulators that the syndicated loan market involves excessive risk-taking and value destruction (Crittenden and Wirz, 2013). The results also show that skin in the game, a core component of post-crisis regulation, is associated with greater value creation by banks. This paper's new measure of risk-adjusted performance can be used by regulators and empirical researchers to separate the impact of any regulation on value creation versus risk-taking.

Although risk-adjusted loan cash-flows capture the value of lending from a financial perspective, the methodology faces certain limitations. The outside option of the bank employees is unobservable, so I cannot directly speak to any labor surplus enjoyed by bank staff. The risk-adjusted performance also does not directly measure the value of the externalities from lending, such as bank lending's contribution to systemic risk (Acharya, 2009).

The broad takeaway is that banks earn economically significant risk-adjusted returns through their screening and monitoring activities, which benefit borrowers and provide compensation for their employees' ability. However, shareholders capture a limited portion of this value. This new evidence helps reconcile empirical findings that bank shareholders receive little value from bank activities (Begenau and Stafford, 2019) with classic theories of banking that emphasize the importance of lending services.

1.1 Related Literature

My paper contributes to a growing empirical literature that analyzes value creation by banks at different stages of the financial intermediation chain. First, Egan et al. (2022) and Begenau and Stafford (2019) analyze the value that banking activities create for their *shareholders*.[4] Second, Flanagan and Purnanandam (2020) analyze the valuation of *government bailouts* of banks, finding that the TARP capital injection provided banks with a heavy subsidy. Another set of empirical papers in this literature analyzes the value of bank loans for *borrowers* (James, 1987; Berger and Udell, 1995; Weston and Yimfor, 2018; Schwert, 2020; Agarwal et al., 2021). James (1987) and Berger and Udell (1995) find that bank borrowers benefit through higher stock market valuation and better loan pricing, providing indirect evidence of banks' screening and monitoring ability. An important recent paper analyzing the value received by borrowers is Schwert (2020), which provides evidence that borrowers are willing to pay higher rates on bank loans than seniority-adjusted bond yields because borrowers value the financial flexibility and option to renegotiate.

In general, these papers study value created on two different sides of the intermediation chain: (i) the value to borrowers (James, 1987; Berger and Udell, 1995; Weston and Yimfor, 2018; Schwert, 2020; Agarwal et al., 2021), and (ii) value to shareholders (Egan et al., 2022; Begenau and Stafford, 2019). What the literature is still missing is an empirical loan-level measure of the value added directly to the *bank* from lending services (e.g., as shown in Figure A.4). My paper fills this gap in the literature. Using this measure, my paper reconciles the empirical findings from Begenau and Stafford (2019) that shareholders receive little value from bank activities with the theoretical literature emphasizing the importance of valuable

[4] Begenau and Stafford (2019) find that the aggregate banking sector, across all its activities, creates zero economic profits for bank shareholders. Egan et al. (2022) find that bank deposit-taking is a much stronger driver of shareholder value creation than lending.

lending services to a bank's business model. Most of the economic profits go to compensate the employees involved in lending, which suggests further research is needed to study the labor involved in providing these traditional banking lending activities (Philippon, 2010; Axelson and Bond, 2015; Bolton et al., 2016; Chen et al., 2022). Although many papers (e.g., Drechsler et al. (2021); Gatev and Strahan (2006); Nagel (2016); Begenau and Stafford (2019); Egan et al. (2022)) examine the specialness of bank *liabilities*, my paper focuses entirely on the value of bank assets through their screening and monitoring activities.

Schwert (2020) studies the borrower's willingness to pay for loans relative to bonds, but this paper differs in several key ways. Conceptually, the borrowers' willingness to pay a higher rate for loans relative to bonds is different from the value added to the bank for two reasons. First, borrowers buy the implicit commitment to renegotiate loans, and the higher price the borrower pays may simply be the fair financial cost for banks to provide that commitment as renegotiations typically involve favorable concessions to borrowers (Roberts and Sufi, 2009; Boot et al., 1993; Mella-Barral and Perraudin, 1997; Chemmanur and Fulghieri, 1994; Eckbo et al., 2022). My replicating cash-flow methodology explicitly selects market benchmarks to resemble the risk profile of frequently renegotiated loan cash-flows to measure the value to the bank net of any financial concessions to the borrower. Second, if the bank screens and monitors a borrower, this can improve the expected loan cash-flows or lower the discount rate relative to what an uninformed investor such as a bondholder would require. Since yields are discount rates on promised cash-flows, either of these effects would result in a lower yield, making bond yields different from the benchmark needed to measure the value to the bank (e.g., see the economic framework in the Appendix). Similar to mutual fund alpha measures, the matched benchmarks reflect whether banks selected better investments or helped improve ex-post loan outcomes. In terms of methodology, the sample in Schwert (2020) is restricted to firms with bonds and detailed capital structure information. My model is general and can be applied to any loan for which ex-post cash-flows are available. This is an important distinction for the cross-sectional analysis because theories suggest banks add more value to smaller, typically unrated firms. Indeed, I show that banks create more value when lending to unrated firms and, in general, firms that face more financing constraints.

More broadly, this paper merges the literature on the risk-adjusted performance of private equity and mutual funds (Carhart, 1997; Berk and Van Binsbergen, 2015; Kaplan and Schoar, 2005; Korteweg and Nagel, 2016; Gupta and Van Nieuwerburgh, 2021), empirical work analyzing bank risk-taking (Meiselman et al., 2020; Benmelech et al., 2012; Fahlenbrach et al., 2018; Keys et al., 2010; Dell'Ariccia et al., 2017; Jimenez et al., 2014; Duchin and Sosyura, 2014), and empirical work testing theories of banking (Sufi, 2007; Ivashina, 2009; Bharath et al., 2011; Gatev and Strahan, 2006). The paper extends the literature analyzing renegotiation in the syndicated loan market (Roberts and Sufi, 2009) by systematically compiling loan refinancings and defaults into a new dataset of realized loan cash-flows. This paper adapts the Gupta and Van Nieuwerburgh (2021) methodology of valuing non-traded private equity claims to pricing the cash-flows of loans. Similarly, Cordell et al. (2021) apply the methodology of Korteweg and Nagel (2016) to value the cash-flows of CLO tranches and study whether CLO investors capture value through their asset portfolio. Although this paper studies syndicated loan cash-flows paid to banks, the methodology can be used to estimate the value created by any bank asset for which realized cash-flows are available. I also extend the methodology from Gupta and Van Nieuwerburgh (2021) to a model-free environment by relying on the law of one price and returns rather than an asset pricing model to construct benchmarks with payoffs similar to loans to price these non-traded claims. I also develop statistical inference for the point estimates in Gupta and Van Nieuwerburgh (2021) by using OLS and applying the bootstrapping procedure from Driessen et al. (2012).

This work complements Philippon (2015), which analyzes the value added of intermediaries from a macroeconomic perspective. I use risk-adjusted returns to take a microeconomic look at the value added for a specific intermediated asset, syndicated bank loans, and analyze heterogeneity in value added across loans.[5] My paper estimates a conceptually cleaner measure of the value added using *risk-adjusted* returns to remove the risk-premium component of income (Wang, 2003). The value added per unit of asset also corresponds to the cost of

[5]Value added in Philippon (2015) is measured using the income for all financial firms in the economy (banks, insurance, private equity, etc.) across all intermediation activites.

intermediation parameter used in many macro-finance models (Hall, 2011; Greenwood et al., 2010; Buera et al., 2011; Gertler and Kiyotaki, 2010) and can be applied to study questions in developmental economics relating to finance and growth (Levine, 1997). My findings have several important implications for these models. For instance, my results on lead bank loan retention inform the relationship between bank leverage and the cost of intermediation and support the predictions of models such as Diamond et al. (2022), Allen et al. (2011) and Holmstrom and Tirole (1997).

1.2 Methodology

1.2 Loan Cash-Flow Data

I construct a dataset of realized cash-flows of syndicated loans in Dealscan. The key data challenge is that, while Dealscan contains detailed information on loan originations and scheduled cash-flows, it has limited information on ex-post prepayments and defaults. To address this challenge, I obtain realized cash-flows by supplementing Dealscan with data on loan prepayments from web-scraped SEC filing and defaults from corporate bankruptcy data.

[See Figure 1.1]

Figure 1.1 outlines this cash-flow construction procedure. I use the amortization schedule and interest rates from Dealscan to construct a series of scheduled quarterly cash-flow payments. If a loan is not prepaid, is not amended, and does not default, then the scheduled cash-flows are the realized cash-flows. Loans are likely refinanced or prepaid, however, before their original maturity. When a loan is refinanced, I assume the balance is repaid, and a new loan observation appears when the refinancing occurred. If a loan is prepaid, the balance is repaid, but no new loan takes its place. Prepayments are an important source of cash-flow variation as the new loans often come with contractual features (i.e., new interest rates). Prepayment timing also matters for detecting defaults from corporate bankruptcy data and applying prepayment penalties.

Sample: I start with a sample of senior term loans to US borrowers in Compustat covered by the Chava and Roberts (2008) linking file. I restrict to sample to term loans because the pay-downs on credit lines are unobservable. I only include floating rate LIBOR loans in the sample as these make up the overwhelming majority of loans in Dealscan. I limit the sample to loans with less than eight years of maturity. Putting an upper limit on the maturity is needed for the tractability of the empirical model and affects the number of years for which I can estimate the risk-adjusted performance. Table 1.1 provides descriptive statistics on the final sample. The sample consists of 8,100 loans and covers over 2 years of loans originated from 1992Q3 to 2014Q1.[6]

[See Table 1.1]

Prepayments: I construct prepayments/refinances from several sources. First, I take refinancing and amendments straight from the Dealscan amendment file. Second, I develop an algorithm to match loans within the same borrower to new loans, which are indicated by Dealscan to refinance previous loans. The algorithm exploits that most loans in Dealscan are modifications of previous loans, as shown by Roberts and Sufi (2009). Finally, I web-scrape 10-K, 10-Q, and 8-K SEC filings to identify prepayments not covered by Dealscan.[7] I check a random sample of 100 loans by reading SEC filings. I find this procedure is 94% accurate at determining loan refinancing/prepayment dates.[8] Table 1.1 shows that 85% of the loans in the sample get refinanced before their stated maturity. This refinancing rate is in line with Roberts and Sufi (2009), which finds that 90% of new originations are modified within Dealscan before their original maturity. The average contractual maturity is 5 years, and the average effective duration is 1.7 years after accounting for the refinancing and prepayments.

[6]The security returns dataset covers 1992Q3 to 2021Q2. 2014Q1 is the last quarter in which all loans are repaid before the end of the return sample in 2021Q2.

[7]Companies are required to disclose any material changes to their debt in SEC-filings. Using web-scraped SEC filings, therefore, enables comprehensive coverage of firms' loan prepayments where Dealscan information is insufficient. See the Appendix for complete details on the loan-matching algorithm and web-scraping.

[8]This procedure allows the correct identification of when a term loan is completely repaid early. There are cases, however, when a loan is partially repaid early, which my methodology cannot detect. Because these repayments are partial, omitting them should have a minimal impact on the cash-flows. This will make the estimates noisier but should not result in any systematic bias of the estimates.

Interest Rates & Fees: I take the interest rate spread over LIBOR from Dealscan and use Compustat financial ratios to compute the spread of loans that use performance pricing.[9] Table 1.1 shows the average interest rate over a 3-month Treasury benchmark is 330 basis points.[10] I assume interest compounds quarterly. If Dealscan indicates a loan is amended, I adjust the cashflows to reflect the new interest rate, amount, maturity, and so forth. I add upfront fees to the cashflows at the time of origination. Berg et al. (2016) shows Dealscan is missing the upfront fees on many loans. I address this by imputing the fees for loans missing the information. In the Appendix, I show that the results are robust to assuming missing loans have no fees. I take prepayment penalty and cancellation fee schedules from Refinitiv Loan Connector.

Defaults & Recoveries: I identify corporate defaults using a combination of bankruptcy databases, including the UCLA bankruptcy database, 8-k filings, and whether a borrower uses DIP/exit financing within Dealscan. I also augment this data with hand-collected information on bankruptcies from web searches. I assume a loan defaults if it is outstanding 90 days before a firm files for bankruptcy. The average loan default rate is 4.5%.[11] I apply recovery rates using industry-by-year loss-given-default estimates from Moody's Annual Default Report. In the Appendix, I report the results are robust to using loan-level recovery rates, which are available from 2005 onward.

Loan Portfolios: After arriving at a series of quarterly cash-flows for each loan, I form loan portfolios by summing the cashflows across all loans originated in a given quarter. Forming loan portfolios allows the empirical estimation to better explain the priced risk in loan cash-flows by diversifying away idiosyncratic risk. Because there are 86 origination-quarters in the sample, there are 86 loan portfolios used in the baseline estimation. For each loan

[9]Ratios used for covenants and performance pricing in Dealscan do not rely on GAAP. Comparing these ratios to comparable metrics in Compustat, therefore, is not always accurate. Demerjian and Owens (2016) show that for most types of covenants, using Compustat ratios maps well to the non-GAAP covenant definitions.

[10]LIBOR is not a risk-free rate. To get an idea of the promised rate of return relative to a risk-free benchmark, I report the average interest rate spread relative to a 3M treasury bond.

[11]This default rate is similar to that of B-rated bonds over the same time period. Figure A.7 in the Appendix plots the volume-weighted default rate over time. The recovery rate for loans is 80% compared to 40% for unsecured bonds.

portfolio, I observe quarterly cash-flow distributions following the origination date. Figure 1.2 plots the quarterly cash-flow distributions of the average loan portfolio in the sample. The figure shows that most of the cash-flow distribution comes within two years of origination, and cash-flows continue until the maximum maturity date of eight years.

[See Figure 1.2]

1.2 Risk-Adjustment Methodology

The Gupta and Van Nieuwerburgh (2021) methodology involves regressing cash-flows on payoffs of securities and using the prices of the securities to discount the cash-flows. I use and build on this methodology to price loan cash-flows. Let R^k_{t+h} denote a cumulative return on a public security k bought at time t and held for h periods. By assuming the law of one price, there exists an SDF such that the pricing equation holds conditionally for these returns:

$$E_t[M_{t,t+h}R_{t+h}] = 1. \tag{1.1}$$

I use this pricing equation to discount loan cash-flows. Let X^i_{t+h} be a cash-flow to a loan portfolio i at h periods after origination at time t, normalized to a \$1 investment. Gupta and Van Nieuwerburgh (2021) estimate the following regression equation of cash-flows on public security payoffs with varying risk exposures at each cash-flow horizon h:

$$X^i_{t+h} = a_{t+h} + b_h R^k_{t+h} + e^i_{t+h}. \tag{1.2}$$

The key identification assumption of the model is that $b_h R^k_{t+h}$ spans all sources of priced risk in the cash-flows. Running this equation is equivalent to discounting cashflows X^i_{t+h} using $M_{t,t+h}$ under this maintained assumption. Constants a_{t+h} are discounted back using the term structure of risk-free rates. The risk loadings b_h receive a price of 1 following the law of one price in (1.1). Equation (1.2) uses returns as payoffs instead dividend/gain strip payoffs as in Gupta and Van Nieuwerburgh (2021). Using returns avoids assumptions about state variables, state dynamics, and SDF parameterization to obtain prices of strip payoffs.

[See Figure 1.3]

Because loan balances are paid down over time, the risk exposures in loan cash-flows are time-varying and depend on the amount of outstanding principal at any point in time. For instance, Figure 1.3 shows the average loan portfolio principal balance is convex, with less than 20% of the balance remaining after four years following origination. To construct benchmarks with similar horizon-varying risk sensitivities to loans, I build on this methodology by instrumenting R^k_{t+h} with a series of loan portfolios' outstanding principal balance $\{z^i_t\}$.[12] This procedure is similar in spirit to Korteweg and Nagel (2016) use of PE benchmark funds to calibrate their SDF estimation. This refinement results in a set of "loan benchmark funds," which implement active investment strategies that mimic the risk factor sensitivity of an amortizing loan. Loan benchmark funds are, therefore, able to span priced loan cash-flows better, which is the key identification assumption of the empirical model. Let z^i_t denote loan portfolio i's outstanding balance normalized by \$1 at time t. I define an instrumented return $\tilde{R}^i_{t+h} = R_{t+h} z^i_t$. The price of an instrumented return is z^i_t:

$$E_t[M_{t,t+h}\tilde{R}^i_{t+h}] = E_t[M_{t,t+h}R_{t+h}z^i_t] = z^i_t. \tag{1.3}$$

I use the loan balance instruments to implement two types of loan benchmark funds that mimic loan portfolios' risk factor sensitivity. First, a rollover investment strategy starts with a \$1 investment in a risky security. At the end of the period, it pays out at any accumulated return. At the start of the next period, the rollover loan benchmark pays out the change in loan balance and reinvests the remaining balance in the same risky security. The strategy repeats until the loan balance reaches zero. The rollover strategy helps span the interest rate payoffs over one-period horizons.[13] Formally, a rollover strategy invests z^i_{t-1} in a security, k,

[12] Instruments here are used in the sense of constructing managed portfolios using realized state variables to assess the performance of actively managed mutual funds (e.g., see Aragon and Ferson (2007)). z^i_t is a valid instrument by construction because z^i_t is in the information set at time t and is constant across payoff horizons h (Cochrane, 2010).

[13] Panel A of Figure A.2 in the Appendix plots an example of the rollover loan benchmark using a portfolio of corporate bonds as the underlying security. The Appendix gives a numerical example of this strategy using the payoff of a corporate bond as the underlying security.

with one-period return $r_{t,t+1}$ at the beginning of the period, pays out any return plus the change in loan principal $z_t - z_{t-1}$ at the end of the period after the return is realized. I define the payoff to this strategy:

$$\tilde{F}^{i,k}_{t+h} = z^i_{t+h-1} r^k_{t,t+h} - z^i_{t+h-1} - (z^i_{t+h} - z^i_{t+h-1}) = z^i_{t+h-1} r^k_{t,t+h} - z^i_{t+h}. \tag{1.4}$$

Intuitively, the investment strategy involves investing \$1 and paying out the interest and balance as the corresponding loan portfolio matures. I formally show the price to implement this strategy at the beginning of the loan is 1. Proof: See the Appendix.

$$E_t[\sum_{j=1}^{H} M_{t,t+j} \tilde{F}_{t+j}] = 1 \tag{1.5}$$

Next, I define a gain investment strategy. A gain benchmark fund invests in a risky security, pays out any change in the loan principal, and reinvests any accumulated returns until a *pre-specified maturity.* It goes short using the same strategy for a risk-free bond.[14] The advantage of the gain benchmark is that it does not pay out accumulated returns until a final maturity date, allowing for horizon-specific loadings, which helps span time-varying default risk and can capture the term structure of default risk as in Gupta and Van Nieuwerburgh (2021). Formally, the gain strategy starts by investing \$1 at time t in security, k, with one-period return $r_{t,t+1}$ and pays out the change in loan principal $z_{t+1} - 1$ at the end of the period.

$$\tilde{L}^{i,k}_{t+1} = r^k_{t,t+1} - (z^i_{t+1} - 1) \tag{1.6}$$

[14]Gain benchmarks are implemented in a long-short fashion to ensure it only distributes cash flows in a single period while still having a return-generating process similar to the risk exposures of a term loan. Going short cancels out cash-flows from the loan principal pay-downs that would otherwise occur before the benchmark's maturity. Panel B of Figure A.2 in the Appendix plots an example of the gain loan benchmark that goes long a corporate bond and short a risk-free bond. The figure also compares the gain strategy to the payoff of an unscaled long-short position, which continues to accumulate returns despite that the loan has been nearly paid down. Later in the paper, I conduct a placebo test in which I apply this methodology to corporate bonds for which I know the true price. In this placebo test, I find that the gain benchmarks are numerically important for correctly pricing corporate bond cash-flows.

The strategy recursively applies the same procedure to the new benchmark balance $\tilde{L}^{i,k}_{t+h-1}$.

$$\tilde{L}^{i,k}_{t+h} = r^{k}_{t+h-1,t+h}\tilde{L}^{i,k}_{t+h-1} - (z^{i}_{t+h} - z^{i}_{t+h-1}) \tag{1.7}$$

The payoff to the gain benchmark strategy long in security k and short the risk-free bond that matures at time $t+h$ by:

$$\tilde{G}^{i,k}_{t+h} = \tilde{L}^{i,k}_{t+h} - \tilde{L}^{i,rf}_{t+h}. \tag{1.8}$$

The price of this self-financing long-short position is 0 for any time horizon h. Proof: see the Appendix.

$$E_t[M_{t,t+h}\tilde{G^{i,k}}_{t+h}] = 0 \tag{1.9}$$

With the prices of these loan benchmarks portfolios in hand, I use them to price the loan portfolio cash-flows. I regress loan cashflows on the payoffs of loan benchmark funds constructed from K public securities.

$$X^{i}_{t+h} = a_{t+h} + \sum_{k=1}^{K}[b^{k}\tilde{F}^{i,k}_{t+h} + c^{k}_{h}\tilde{G}^{i,k}_{t+h}] + e^{i}_{t+h} \tag{1.10}$$

Rollover benchmarks $\tilde{F}^{i,k}_{t+h}$ have one coefficient, and gain benchmarks $\tilde{G}^{i,k}_{t+h}$ have a coefficient for each maturity horizon h. I take the risk-adjusted profit, RAP, of the loan cashflows by applying the prices of the above investment strategies and discounting residuals with the risk-free term structure.

$$RAP^{i}_{t} = \sum_{h=1}^{H} P^{\$}_{t,h}a_{t+h} + \sum_{k=1}^{K} b^{k} + \sum_{h=1}^{H} P^{\$}_{t,h}e^{i}_{t+h} - 1 \tag{1.11}$$

I show this measure is equivalent to discounting the loan cash-flows using M_{t+h} by using the loan benchmark prices calculated above.

$$
\begin{aligned}
&E_t[\sum_{h=1}^{H} M_{t,t+h} X_{t+h}^i] = E_t[\sum_{h=1}^{H} M_{t,t+h}(a_{t+h} + \sum_{k=1}^{K}[b^k \tilde{F}_{t+h}^{i,k} + c_h^k \tilde{G}_{t+h}^{i,k}] + e_{t+h}^i)] \\
&= \sum_{h=1}^{H} P_{t,h}^{\$} a_{t+h} + \sum_{k=1}^{K} b^k + E_t[\sum_{h=1}^{H} M_{t,t+h} e_{t+h}^i] \approx \sum_{h=1}^{H} P_{t,h}^{\$} a_{t+h} + \sum_{k=1}^{K} b^k + \sum_{h=1}^{H} P_{t,h}^{\$} e_{t+h}^i
\end{aligned}
\tag{1.12}
$$

The last term is the risk-adjusted profit from Gupta and Van Nieuwerburgh (2021). The last equation holds exactly when e_{t+h}^i is orthogonal to $M_{t,t+h}$ or the variance of e_{t+h}^i approaches zero. This condition is true if the benchmark funds span all sources of priced risk in the cash-flows. Under this assumption, the risk-adjusted profit prices the loan cash-flows using $M_{t,t+h}$. A reasonable interpretation is that the risk-adjusted profit measures the NPV of the loan cash-flows from the bank's perspective since a burgeoning empirical literature supports that banks are the marginal investor in stock and bond markets (Adrian et al., 2014; He et al., 2017; Kargar, 2021). An alternative economic interpretation is that Equation (1.10) is equivalent to estimating a replicating portfolio that mimics the payoffs of loan cash-flows. The loan RAP is positive if the price of spanning the cash-flows with the replicating portfolio is more expensive than the \$1 required to invest in the loan portfolio.

I focus on measuring the unconditional risk-adjusted performance. Using the estimated coefficients from (15), I compute the unconditional mean RAP:

$$
\widehat{RAP} = E[E_t[\sum_{h=1}^{H} M_{t,t+h} X_{t+h}^i]] - 1 = \sum_{h=1}^{H} \bar{P}_{t,h}^{\$} \hat{a}_{t+h} + \sum_{k=1}^{K} \hat{b}^k - 1. \tag{1.13}
$$

Estimating the unconditional RAP requires the weaker assumption that the residuals are unconditionally orthogonal to the SDF.[15] I subtract the normalized \$1 it costs to invest in the loan portfolio to reflect the difference between buying the replicating portfolio and investing in bank loans. I arithmetically annualize the risk-adjusted performance by dividing

[15]Estimating $RAP = E[E_t[\sum_{h=1}^{H} M_{t,t+h} X_{t+h}^i]] - 1$ with (13) only requires that $Cov(M_{t,t+h}, e_{t+h}^i) = 0$ rather than $Cov_t(M_{t,t+h}, e_{t+h}^i) = 0 \ \forall t$. This relaxed assumption is more feasible as the loadings in (10) are not time-varying.

by the ex-post duration of the loan portfolio cash-flows:

$$\widehat{\psi} = \frac{\widehat{RAP}}{Duration}. \tag{1.14}$$

$\widehat{\psi}$ is the annualized risk-adjusted return and directly measures the value-added on \$1 of loan per year. Using the unit value-added, I can also compute the dollar amount of value-added per year by multiplying the risk-adjusted return by the corresponding size of the loan portfolio.[16]

1.2 Factor Selection & Empirical Implementation

In the empirical analysis of the paper, I estimate Equation (1.10) and use the loadings to compute the value added, ψ. First, I describe the empirical choices I make to estimate the model. I use quarterly loan cash-flows and returns, and I specify yearly horizon coefficients h to reduce the number of coefficients I must estimate. Below I describe the public securities that I use to span loan cash-flows. For each of these factors, I construct loan benchmark portfolios that implement the rollover and gain investment strategies by dynamically investing in these securities.

Risk-Free Asset: I include a rollover loan benchmark that invests in a risk-free bond. This benchmark is analogous to the payoff of a risk-free floating rate bond.

Duration Risk: The horizon intercept coefficients a_{t+h} in Equation (1.10) correspond to investing in risk-free zero-coupon bonds of varying maturities.

Credit Risk/Liquidity Risk: I include multiple corporate bond portfolios in the spirit of Bai et al. (2019) to capture variation in credit and liquidity risk. First, I use the returns on a value-weighted portfolio of corporate bonds. I include value-weighted returns on a portfolio of the lowest quintile of corporate bonds by credit rating (Bai et al., 2019). I include

[16]Because the unit of analysis is a loan rather than a bank (i.e., a bank can have multiple loans in its portfolio), this unit value-added measure is broadly comparable across loans of different sizes without being affected by decreasing returns to scale (Berk and Van Binsbergen, 2015). To further demonstrate this point, I show that the main results remain unchanged when I control bank size and loan size in the robustness tests in Table 1.10. Additionally, the cross-sectional predictions I test are in terms of unit value added rather than the dollar amount.

value-weighted returns on the lowest quintile of the downside risk factor in (Bai et al., 2019).[17]

Prepayment Risk: I use the returns on a value-weighted portfolio of callable corporate bonds.

Stock Factors: I also include stock factors that can capture an additional source of credit risk. I include the CRSP value-weighted market return, the top quintile book-to-market portfolio, and the bottom quintile size portfolio (Fama and French, 1993).

Broadly, this choice of benchmarks corresponds to empirical evidence on the risk factors of bank investment portfolios (Begenau et al., 2015). With the payoffs and prices of these investment benchmarks, I estimate equation (1.10) with OLS and compute the unconditional RAP for the portfolio using equation (1.13). Once I obtain the RAP estimates, I compute ψ by annualizing RAPs using the ex-post duration of the loan portfolio cash-flows using Equation (1.14).[18]

I report the mean value added ψ throughout the results section. Gupta and Van Nieuwerburgh (2021) does not provide a method to conduct statistical inference for the point estimates. To do so, I estimate the model with OLS and apply the non-parametric block bootstrap procedure from Driessen et al. (2012) to obtain standard errors. I re-sample the loans with replacement within each loan portfolio using 50 replications. For each resampling, I estimate (1.10) and compute the mean ψ to construct an empirical distribution, from which I obtain standard errors.[19]

In the cross-sectional tests, I form portfolios of loans sorted by borrower and lender characteristics. For each portfolio, I sum all loan cash-flows originated in a given quarter and characteristic bucket. For instance, if there are 86 origination quarters and I group loans into two buckets of borrower size, there will be 172 loan portfolios. For each characteristic bucket, I estimate equation (1.10) separately, allowing for different risk-exposure loadings to

[17]See the Appendix for a detailed description of corporate bond return data. I extend corporate bond returns data to 1992 using NAIC and Datastream bond prices. In the Appendix, I also show the results are similar when I include the Pástor and Stambaugh (2003) liquidity factor.

[18]I compute the duration of each loan portfolio by discounting at the risk-free rate and taking the weighted average duration using the risk-free discounted values as weights.

[19]As an alternative procedure, I estimate standard errors using a stack-covariance matrix clustered by loan origination quarter and apply the delta-method applied to the sum of coefficients. I find similar results and levels of statistical significance using this method.

capture cross-sectional differences in value added. Likewise, I apply the Driessen et al. (2012) non-parametric block bootstrap for standard errors in cross-sectional tests.

1.3 Results

1.3 Baseline Estimation

I begin by describing the baseline estimation. I estimate Equation (1.10) using OLS by regressing the loan portfolio cash-flows on loan benchmark funds investing in the chosen public securities. I report the loadings on rollover benchmarks and the *sum* of the loadings across investment horizons on the gain strategies. I also report the sum of the loadings across the investment horizons on the zero-coupon risk-free bonds. Zero-coupon bond loadings correspond to investment horizon fixed effects in the model. In Figure 1.4, I plot the zero-coupon and gain strategy loadings by their investment horizons. I use the estimated risk exposures to compute the risk-adjusted return ψ and its standard errors using the bootstrap procedure.

[See Figure 1.4]

Table 1.2 contains the results. The first column estimates the model using risk-free bonds, the corporate bond market, credit risk (CRF), and downside risk (DRF) benchmarks. The estimates show that the loan portfolios load \$0.97 on the risk-free floating bond rollover benchmark and \$0.08 on the corporate bond market rollover benchmark. There are also small negative loadings on the CRF and DRF rollover benchmarks. Most of the loan cash-flows variation is explained by investments in the risk-free floating rate benchmark. This loading is sensible since all loans in the sample use a LIBOR floating rate. The first model also loads on zero-coupon bonds, and there is a positive coefficient on the corporate bond gain strategy, indicating there is an important source of horizon-varying risk in the loan cash-flows. The model's R^2 is over 99%, which supports that the loan benchmark funds successfully span the cash-flows. The corresponding risk-adjusted estimate is 209 basis points per annum. This estimate is highly statistically significant. The economic magnitude of 209 basis points is large and indicates that banks create just over $0.02 of value per year on every dollar of loan.

[See Table 1.2]

Next, I add more factors to the model to include a broader range of priced risk factors. The second column introduces callable corporate bond benchmarks to the specification. I find positive loadings on the callable gain benchmark, and the other loadings remain similar.[20] Overall, the model suggests that including callable bonds helps span the priced risk in loan cash-flows, consistent with theoretical and empirical evidence that renegotiation and prepayment are important sources of risk in loans (Boot et al., 1993; Mella-Barral and Perraudin, 1997; Roberts and Sufi, 2009). The risk-adjusted return estimate reduces to 198 basis points per annum, consistent with the added factors capturing additional sources of priced risk.

In the third column, I add stock market returns to the model, including the CRSP VW market, a portfolio of high book-to-market stocks, and small market-equity stocks. There are some gain loadings on the CRSP market benchmarks, but they do not significantly impact the level of the risk-adjusted return. The risk-adjusted return estimate remains similar at 191 basis points.[21] Figure 1.4 plots the zero-coupon and gain strategy loadings estimated from this specification by their investment horizons. The figure shows that loan cash-flows load heavily on the gain investment strategies going long in corporate bond securities in years 3 to 5 following loan origination, consistent with default risk mattering for loans a few years after origination. Together with loadings on the risk-free bond rollover investment strategy, the overall replicating portfolio resembles a risk-free bond plus a credit spread component investing in risky corporate debt.

[20] One exception is the corporate bonds gain factor becomes negative. This sign flip is because the benchmarks in this exercise are not orthogonalized, and the corporate bond market benchmark is correlated with the callable benchmarks. This does not pose a problem for estimating the risk-adjusted return because the purpose is to predict and span the cash-flows rather than identify individual risk factors.

[21] To calculate the implied credit spread from this model, I re-estimate this model after setting loss-given-default to 0%. I find that the model implies a credit spread of 140 basis points for the loan sample. Details of this calculation are in the Appendix.

The 190 basis point estimate implies that banks create \$0.019 in value added per \$1 of loan outstanding each year. To convert these estimates to dollars, I multiply this unit value added by the outstanding loan sample balance. Across the sample period, the average outstanding loan balance is \$176 billion, which implies an average value creation of \$3.3 billion per year. If I extrapolate this estimate to the full sample of C&I loans originated by all banks covered by the FRY-9C call reports, I find that banks create on average \$22.7 billion in value each year for commercial loans. This is a conservative bound on the total value created as syndicated loans are less informatively intensive than commercial loans in general. Overall, banks produce a very large economic magnitude of value through commercial lending.

1.3 Financial Constraints

I now begin a series of cross-sectional tests to examine heterogeneity in the value across loans in line with theories of financial intermediation. To conduct these tests, I form equal-weighted buckets of loan portfolios sorted by the borrower and bank characteristics.[22] For each bucket, I re-estimate risk exposures, resulting in risk-adjusted return estimates for each set of characteristic-sorted portfolios.

First, I test whether banks earn more risk-adjusted returns when lending to financially constrained borrowers, for which classic theories predict there is greater scope for screening and monitoring (Leland and Pyle, 1977; Ramakrishnan and Thakor, 1984; Diamond, 1984; Fama, 1985). To capture a borrower's financial constraints, I use four simple measures following the existing literature: firm size, firm age, whether the firm has issued a corporate bond, and whether the borrower has a long-term credit rating (Hadlock and Pierce, 2010; Sufi, 2007; Chava and Purnanandam, 2011). When borrowers are smaller, younger, unrated, and have not previously tapped capital markets, there is more potential for moral hazard and adverse selection that can lead to financial constraints. I consolidate these four measures

[22] In cross-sectional tests, I implement equal-weighted loan portfolios because the purpose of the exercise is to determine how the unit value added varies for an average loan in a sample across different covariates. Equal weighting in this empirical setting does not suffer from issues of portfolio re-balancing because all investments are fixed at the time of origination. In the Appendix, I report the results of cross-sectional tests using value-weighted portfolio buckets. The mean unit value added is higher for equal-weighted portfolios because the average promised return is also higher.

into a single measure of financial constraints by taking the first principal component and use it to form four quartile-sorted buckets of loan portfolios.[23]

Theory suggests a few ways how risk-adjusted returns should vary with borrowers' financial constraints. Classic theories suggest banks should create more value when they provide more intense information production and monitoring for borrowers with more severe constraints (Leland and Pyle, 1977; Ramakrishnan and Thakor, 1984; Diamond, 1984; Fama, 1985). Second, theories of excessive risk-taking suggest that bank shareholders can maximize their option value by exploiting government guarantees and offloading risk to creditors (Keeley, 1990). To maximize their option payoff, bank shareholders invest in projects that are negative NPV from a public market benchmark perspective: banks destroy value. For banks to take excessive risk, they must lend to opaque, financially constrained firms, whose riskiness is less observable to markets and regulators. Third, theories such as Hanson et al. (2015) and Dang et al. (2017) predict a complementary between opaque loans and issuing liquid liabilities, which command a convenience yield from investors. These theories, therefore, also predict banks are willing to accept a lower return on loans to more opaque, financially constrained borrowers.

Table 1.3 reports the results. The first panel reports the risk-adjusted return for each portfolio bucket and the overall equal-weighted average across the four portfolios. Banks earn 66% higher risk-adjusted returns on loans to the top quartile of financially constrained borrowers compared to the bottom quartile, and the difference is statistically significant. This finding is consistent with the classic view that banks earn more value when engaged in more intense screening and monitoring of financially constrained borrowers.

[See Table 1.3]

[23] Specifically, I take the first principal component of -1*log(total assets), -1*(firm age), an indicator whether the firm has issued a corporate bond, and an indicator for whether the firm is unrated. I add a negative sign to assets and age since smaller and younger firms are more opaque and require additional monitoring. The first principal component explains over 50% of the variation in firm unrated, firm size, and firm issued bond and over 30% of the variation in firm age.

1.3 Competition & Rent Extraction

One concern with the previous test is whether the higher risk-adjusted returns are driven by the bank's market power over more constrained borrowers. In a competitive lending market, the value from screening and monitoring should be just enough to cover the economic costs of labor and other expenses to provide these services. In contrast, if the lending market is not competitive, banks can extract rents from borrowers, earning more than enough value to compensate for the costs. To distinguish between these two sources of risk-adjusted returns, I examine bank lending relationships, which have sharp predictions about these channels.

The classic view of relationship banking predicts that lenders acquire additional information on the borrower as the relationship progresses, decreasing the cost of screening and monitoring that borrower (Berger and Udell, 1995). The extent to which there is competitive lending pressure, banks should earn less value, reflecting the lower costs of lending (Petersen and Rajan, 1994; Schenone, 2010).[24] In contrast, theories such as Rajan (1992) and Sharpe (1990) predict relationship lenders extract informational rents from borrowers because they hold an informational monopoly when they are the sole lender. The bank can extract an informational rent because it can screen and monitor at a lower cost than other lenders who cannot access the relationship bank's information. Sharpe (1990) predicts that lenders begin extracting rents later into the relationship, whereas lenders set loan pricing more competitively at the beginning of the relationship. These theories predict that banks extract more value from borrowers via informational rents when the relationship is more developed. Similarly, theory predicts that information and monitoring costs decrease in the proximity between lenders and borrowers. In contrast, closer lenders can also extract more market power from borrowers (Degryse and Ongena, 2005).

I carefully construct empirical measures of bank-borrower lending relationships that correspond to these theories. To capture the 'relationship intensity,' I use the Bharath et al. (2011) measure of the fraction of a borrower's loans from the same lender over the past five

[24] This argument requires that the information produced by the bank spills over to other potential lenders, generating competitive pressure.

years. I construct a variable 'any relationship' equal to one if a borrower has used the lead lender in a previous loan as a lead lender. I also measure the length of time a borrower has used a particular lead bank. Finally, I look at the physical distance in miles between lenders and borrowers and take negative times the distance as a measure of 'Proximity.'

[See Table 1.4]

Table 1.4 contains the results. I find borrowers with more intense lending relationship intensity have 29% lower risk-adjusted returns. This negative effect is consistent with relationship lenders competitively earning less value since they have lower screening and monitoring costs. Similarly, having any relationship and the length of a relationship are both negatively associated with value added, consistent with theories that a lending relationship reduces informational frictions and lowers the cost of monitoring. Value added is significantly lower for borrowers located closer to the lenders, consistent with the cost-based explanation. In the Appendix, I also report that I find no association between banks' industry market concentration and risk-adjusted returns. These results support the favorable view of relationship lenders and suggest that banks earn value to cover the monitoring costs, benefiting the borrower rather than extracting rents through informational holdups.

1.3 Bank Incentives

To complement the tests on borrower financing frictions, I also examine how the bank's incentives to screen and monitor affect risk-adjusted returns. Lenders face agency conflicts and receive government guarantees that can diminish their incentives to screen and monitor borrowers (Holmstrom and Tirole, 1997; Ivashina, 2009; Allen et al., 2011; Diamond et al., 2022). These theories emphasize that banks must hold substantial skin in the game to be incentivized to provide lending services. Therefore, banks must retain more of a loan when originating loans that require more intense screening and monitoring services. As a result, I expect the value of loans to be higher when they retain more of the loan and have stronger incentives.

I measure skin in the game using the fraction of the loan the bank retains on its balance sheet at origination.[25] A bank's balance sheet retention affects how a bank internalizes the payoffs of monitoring. I also take the Herfindahl index of the syndicate ownership structure to measure the joint incentives of lenders to engage in screening/monitoring of the borrower. Sorting with these characteristics, I form four loan portfolios. Table 1.5 presents the results. Loans in the top quartile of lead lender retention have 31% higher risk-adjusted returns compared to the bottom quartile. Similarly, loans with a more concentrated syndicate structure have 57% risk-adjusted returns. These results suggest that skin in the game and syndicate structure incentivizes banks to screen and monitor their borrowers, producing more value.

[See Table 1.5]

To further shed light on the economic mechanism, I investigate whether banks retain more of the loan on the balance sheet when they lend to firms with a greater need for screening and monitoring. I test this by regressing the measure of borrower constraints on the bank syndicate structure measures, controlling for time-fixed effects. Table 1.6 shows the results. Banks retain more skin in the game and the ownership structure is more concentrated when lending to constrained firms, further supporting that providing intermediation services requires ensuring bank incentives. Overall, the results so far indicate that both the borrowers' need for monitoring and banks' incentives to monitor matter for the value of bank loans.

[See Table 1.6]

1.3 Borrowers' Value From Loans

Are borrowers better off when the bank creates more value? By revealed preference, the borrower will only take the loan if it's weakly better than its alternative financing choices.

[25] According to recent empirical evidence presented in (Blickle et al., 2020), term loan B's are frequently paid off soon after origination. Although term loan B's only represent a fraction of the overall sample, both theoretical and empirical evidence suggests that lead bank retention at origination can be used as a proxy for the bank's screening incentives, since there is pipeline risk that they will be unable to sell it (Gryglewicz et al., 2021). In addition, I capture the lead bank's overall incentives to monitor by measuring lead retention using the lead bank's total exposure to a loan package and not just the individual facility.

This means the value of loans held by the bank is a lower bound on the total social value shared between the bank and borrower. To quantify how large the borrowers' benefits from a loan are, I analyze how borrowers' cost of capital changes after receiving a loan. First, a borrower can directly benefit if a loan provides a lower cost of capital relative to alternative types of finance. To measure this direct benefit, I examine loan-bond spreads, the difference between the interest rate spread on a loan and a matched bond yield from the closest bond issued by the borrower just before the start of the loan facility (Agarwal et al., 2021).[26] This measure benchmarks the price of a loan to a borrower's cost of finance in the bond market just before the loan was issued, capturing the differences in frictions that a borrower might face in the financial market without using a bank.

Second, a loan can indirectly benefit borrowers by lowering their cost of capital in other markets. For instance, the classic paper by James (1987) shows borrowers experience positive abnormal returns upon announcing that they obtained a loan. To measure these indirect benefits, I comprehensively collect new articles on announcements of loans in the sample and compute cumulative abnormal returns around the loan announcement date following James (1987).[27] Similarly, I repeat this event study analysis for bonds and measure the difference in bond yields around the announcement date. These measures capture how banks' informational content and monitoring abilities can spill over and lower the firm's cost of capital in other financial markets (Weston and Yimfor, 2018).

I regress the borrower cost of capital measures on financial constraints from the previous tests to analyze the pattern in borrowers' and lenders' value from lending. Table 1.7 contains the results. The first and second panels examine the abnormal stock returns and changes in bond yields around loan announcements, respectively. In the first column, I report the levels of abnormal stock returns. Replicating the principal finding of James (1987) for the sample,

[26] I use the offering yields of bonds issued 120 days before the start of the loan facility and not including bonds issued after the loan to avoid spillover effects that obtaining a loan has on bond pricing. I subtract the risk-free term structure from bond yields because loans have floating rates and compute the loan-bond spread as the difference.

[27] I take a seven-day event window centered on the publication date of the article indicating that a bank has obtained a loan. I use this seven-day window to compute stock CARs using the market bond and the difference in bond yields using TRACE transaction data over the same seven-day window.

I find that firms receive positive and statistically significant abnormal stock returns of 89 basis points around the loan announcement. Similarly, bond yields decrease by an average of 8 basis points upon the loan announcement. Although the bond spillover effects measured in yields are quantitatively small compared to the 190 bps that the value banks gains on $1 of lending, this effect can be potentially very economically significant in a weighted average cost of capital sense because a firm's amount of outstanding public bonds frequently exceeds the loan amount. Moreover, the announcement effect is likely a lower bound on the true effect because the firm would also face a higher cost of capital from the news that it has increased its leverage, and markets may have already incorporated other information content from a firm's bank loans. In the cross-section, the effects are larger when the firms are more constrained: firms experience significantly larger stock announcement returns and a larger decline in bond yields.

[See Table 1.7]

The third panel examines loan-bond spreads. The first two columns show that more financially constrained borrowers have significantly lower loan-bond spreads, indicating that these borrowers benefit relatively more from loans, consistent with the findings of Agarwal et al. (2021). This correlation is robust to controlling for many risk characteristics, including capital structure, stock volatility, stock return, and return on assets.[28]

Together, these results paint a clear picture: When banks lend to financially constrained borrowers with more need for screening and monitoring, they increase the total social value by earning risk-adjusted returns and lowering the cost of finance for borrowers. Overall, the evidence shows that the value of bank loans is driven by the banks' cost-based provision of screening and monitoring that help mitigate the financial frictions of borrowers. Value creation for banks does not make borrowers worse off.

[28] I focus on the cross-sectional variation instead than levels of loan-bond spreads due to differences in the seniority of these securities (Schwert, 2020; Agarwal et al., 2021). I include several controls to account for cross-sectional differences in price because of seniority.

1.3 Distribution Among Bank Stakeholders

How is the value distributed among banks' stakeholders? Because the measure of risk-adjusted returns is taken at a "gross" level (i.e., before payouts to any of the bank stakeholders), it is useful to understand how much income flows to shareholders and how much goes to compensate managers. To understand the division, I estimate the expense ratio of commercial lending. The key challenge in constructing this estimate is that banking datasets like FRY-9C report the total non-interest expense of the bank but not the expenses attributable to commercial lending. The average bank's total non-interest expense is 300 bps; however, some of these expenses may also reflect the high costs of trading and providing deposit liquidity services, which are extraneous to the expenses of commercial lending. To overcome this difficulty, I follow the hedonic regression approach of Hanson et al. (2015) to obtain an estimate of a hypothetical bank whose only assets are commercial loans and whose liabilities consist only of wholesale funding and equity. Using FRY-9C data on bank holding companies over 1994 to 2014, I estimate the following pooled hedonic equation using banks' total non-interest expenses, compensation expenses, and other operational expenses as the outcome variables:[29]

$$\frac{Expense_{it}}{Asset_{it}} = a + \sum_{k=1}^{K} b^{(k)} \frac{Asset_{it}^{(k)}}{Asset_{it}} + \sum_{j=1}^{J} c^{(j)} \frac{Deposit_{it}^{(j)}}{Asset_{it}} + dX_{it} + e_{it}. \tag{1.15}$$

Following Hanson et al. (2015), I include commercial loans, real estate loans, consumer loans, other loans, and trading assets as the k asset categories. I include transaction deposits, saving deposits, foreign deposits, and other liabilities as the j deposit categories. The omitted liabilities categories are equity, time deposits, commercial paper, fed funds purchased, and securities sold under agreement to repurchase. I also include bank size, off-balance sheet items, and non-interest income as controls in X_{it}. The expense ratio specific to commercial

[29] I exclude 'Goodwill impairment losses' and 'Amortization expense and impairment losses for other intangible assets' from the FRY-9C definition of non-interest expenses. I drop banks with negative expense ratios or banks with expenses above the 98% percentile as the data to exclude banks in FRY-9C with very large expense ratios over 10000 bps.

lending is estimated as $\hat{a} + \hat{b}^{(CommercialLoan)}$, which is the expense ratio that corresponds to a hypothetical bank that uses entirely wholesale funding and invests only in commercial loans.[30]

[See Table 1.8]

Table 1.8 presents the estimates from this exercise. The estimated total non-interest expense for commercial lending is 164 basis points.[31] I further decompose this total into 108 bps to staff compensation and 55 bps to non-compensation operational expenses. Based on these estimates, 26 bps of the 190 bps in risk-adjusted returns flow to shareholders. Because the standard errors of the risk-adjusted returns and total non-interest expense are both roughly 20 bps, the 26 bps of economic profits to shareholders is not statistically different from zero. Even if I cannot conclude that value flows to shareholders, these findings are analogous to Berk and Van Binsbergen (2015) and support that banks are skilled at producing information and monitoring when lending. These calculations are consistent with most of the risk-adjusted income going to compensate loan officers and managers for their labor involved in screening and monitoring. This evidence is consistent with the role of bank employees in being paid to alleviate firms' financing frictions as in Philippon (2010).

1.4 Robustness Tests & Discussions

1.4 Corporate Bond Cash-Flow Placebo

I test the baseline model using the cash-flows of a class of securities for which I know the true price: corporate bonds. A concern with the baseline model is whether or not it

[30]This estimate represents the average expense ratio for a commercial lending bank in FRY-9C data. The calculation assumes that the expense ratio per asset on a bank's balance sheet is comparable to the per asset return on a syndicated loan. This assumption is reasonable insofar as banks participate in multiple loan syndicates as both lead arrangers and participants, and the balance sheet expense ratio captures the average expense for a dollar of commercial loan. It is also possible that the average expense per balance sheet loan overestimates the expense ratio since the lead bank only keeps a fraction of the loan on its balance sheet. In this case, I underestimate the value that flows to shareholders.

[31]In Appendix Table A.4, I report how the estimated expenses change with alternative assumptions and sub-samples. Broadly speaking, the magnitude and division of surpluses do not change with these alternative estimates. I demean size to evaluate the commercial lending expense for the average bank size in the sample. I show that the expenses are smaller when I re-estimate the model on a sample of larger banks.

successfully spans all price risk factors in the loan cash-flows. To get an idea of how successful the model is, I repeat the baseline exercise by forming portfolios of corporate bonds and pricing them using the same approach but with benchmark funds imitating the principal balance of corporate bonds. Like loans, the primary source of priced risk in corporate bonds is default risk. Therefore, testing corporate bonds helps determine whether the public benchmarks can correctly price default risk.

I form corporate bond cash-flows using the same filters for the corporate bond returns and keep corporate bonds with moderate default risk (BBB-B rating) with four to eight years of remaining maturity.[32] I compute defaults from the Mergent FISD default file and WRDS bond returns and use trading prices to determine recovery rates. Although the returns and cash-flows come from the same set of bonds, this is a nontrivial test since it determines whether security returns can span the cash-flows of a similar instrument. Unlike loans for which I use the investment amount to normalize a $1 investment, I use the transaction price I observe in TRACE or NAIC to perform this normalization. The null is that corporate bond portfolio cash-flows have zero value-added, equivalent to saying they are correctly priced and that a public market investor investing in them earns no economic profits.

[See Table 1.9]

Table 1.9 shows the results of this exercise. Because corporate bonds are fixed-rate, I use a fixed-rate investment strategy to replace the floating strategy used for loans.[33] More interesting, however, is whether the benchmarks can span the default risk in the loan placebo. I find large loadings on the gain corporate bond and credit risk factor benchmarks. Like the loan estimate, I find evidence that the benchmark portfolios are good at spanning the cash-flows with an R^2 over 99%. Most importantly, I find no statistically significant risk-adjusted returns in line with the null hypothesis that the benchmark funds correctly price

[32]I also require that the bonds are non-callable because information on bond calls is limited. Over 75% of the loans in the sample also have an original contractual maturity of four to eight years. I allow the same bond to enter the sample multiple times because I observe their prices at multiple dates with different remaining maturities.

[33]This benchmark buys the promised coupon payments using zero-coupon treasury bonds.

the cash-flows. Regarding the economic magnitude, the final column that includes stock factors finds a risk-adjusted return of only seven bps. I also find that this approach produced statistically insignificant results when I estimate the model separately for bonds of different credit ratings (B-BBB), supporting that the model captures cross-sectional differences in credit risk.

1.4 Loan Level Analysis With Controls

Next, I estimate the risk-adjusted returns using loan-level cash-flows rather than pooling loans into portfolios. An advantage of the loan-level estimation is that I can introduce loan-level controls to the analysis. Like the portfolio tests, I still form characteristic-sorted buckets of loans, for which I separately estimate risk exposures. Let i correspond to an individual loan cash-flow stream, and j correspond to the loans' risk-exposure category (for instance, there are four buckets of loans sorted by borrower financial constraints). Unlike the baseline tests, which estimate the unconditional risk-adjusted returns pooled into portfolios, I estimate the *loan-level* risk-adjusted returns by applying the assumption from Gupta and Van Nieuwerburgh (2021) that all cash-flows with a given category share the same risk-factor exposures. I obtain loan-level risk-adjusted return estimates by adding discounted residuals to the unconditional risk-adjusted profit:

$$\widehat{RAP^{i,j}} = \sum_{h=1}^{H} P^{\$}_{t,h} \widehat{a}^{j}_{t+h} + \sum_{k=1}^{K} \widehat{b}^{j,k} + \sum_{h=1}^{H} P^{\$}_{t,h} \widehat{e}^{j,i}_{t+h}. \tag{1.16}$$

Realistically, all loans in the same j category do not share the same risk exposures. However, like the portfolio test, I am only interested in how risk-adjusted returns vary, on average, across j, which have separately estimated risk exposures. The advantage of this approach is that I can now control for loan-level covariates that vary by i. Specifically, I estimate the following regression equation:

$$\widehat{RAP^{i,j}} = a + bPS_j + cZ_{i,j} + u_{i,j}. \tag{1.17}$$

PS_j is an indicator variable for loan categories j. I am interested in estimating b, which measures how risk-adjusted returns vary across risk-sorted categories of loans conditional on a vector of loan level controls $Z_{i,j}$. Of course, $\widehat{RAP^{i,j}}$ is generated by the previous estimation, so I estimate the entire procedure within a bootstrap to obtain standard errors for $\hat{b}$.

[See Table 1.10]

Table 1.10 shows the results. The baseline risk-adjusted return using the loan-level estimation is 150 basis points, which is very similar in magnitude to the portfolio-level estimate.[34] In Column (2), I sort loans into two categories based on whether they have above or below median 'Relationship Intensity,' as defined in Table 1.4. I then control for the first principal component of financial constraints, log loan size, loan maturity, bank size, the firm's ratio of debt to assets, and the firm's interest coverage ratio. The estimate shows banks earn 84 basis points lower risk-adjusted returns when lending to firms with which they have intense relationships. The point estimate is statistically significant and identical to the analogous portfolio-level test of 84 basis points. Importantly, the included covariates indicate that differences in loan size, bank size, and levels of financial constraints cannot explain away the association between risk-adjusted returns and relationship intensities. The third through fifth columns have similar results, showing that the main results of the paper are robust to including these loan-level controls.

1.4 Loan Cash-Flow Robustness

This section reports how the baseline risk-adjusted return estimates change when I use different assumptions/sub-samples to construct realized loan cash-flows. Even if the cash-flows are measured with error, it should not affect the cost estimates if the error does not systematically covary with priced risk factors. The key assumptions to construct loan cash-flows are as follows: (i) the loan recoveries vary by year/industry, (ii) the amortization schedule is imputed for loans with no payment schedule on Dealscan, and (iii) the upfront fee is imputed if it is missing from Dealscan.

[34]The difference in the estimates can be partially attributed to different weights across loan portfolios. There are a different number of loans in each portfolio, and this weighting will influence the baseline estimate. In contrast, the portfolio estimates equally weight all loans across the sample.

Table A.3 shows how the baseline estimate changes when I relax these assumptions to estimate risk-adjusted returns. The table shows that risk-adjusted returns do not substantially vary when I re-estimate risk-adjusted returns on these sub-samples with different assumptions. Additionally, the main cross-section results remain robust to these specifications.

1.4 Test For Omitted Factors

In the Appendix, I conduct the Gagliardini et al. (2019) test to see whether the included benchmark funds constitute an approximate factor structure or whether there is an unaccounted risk factor. The idea behind the test is the eigenvalue of the cash-flow errors across a set of test assets is informative of some common omitted factors not spanned by the benchmarks. Using this test, I cannot reject the null hypothesis that the factor structure is correctly identified and there is no omitted factor.

1.4 Collinearity and Elastic Net

I also estimate the baseline specification using elastic net instead of OLS. Using elastic net addresses the concern that there is high multicollinearity between the different loan benchmark funds because they are all instrumented by the same loan balance variable. For this paper's purpose, collinearity between the benchmark funds is not an issue because the goal is to identify a sum of regression coefficients rather than individual coefficients. Nevertheless, elastic net is well suited to address multicollinearity problems because it can shrink the dimension of relevant risk factors while keeping the most relevant ones. Table A.3 shows that the baseline risk-adjusted return increases to 210 basis points when I estimate with elastic net: Using OLS results in a conservative estimate of the risk-adjusted returns. The out-of-sample R^2 remains high and over 99%. The cross-section results are stronger when I estimate them using elastic net.

1.4 Liquidity Premium

One concern is that part of the bank's risk-adjusted income may be due to a liquidity premium since the sample loans do not trade in capital markets like the benchmark assets. How much of the 191 bps of risk-adjusted returns can be explained by liquidity? Comparing investments with near-identical cash-flows that do and do not trade in markets (e.g., Treasury bonds versus certificates of deposits) implies investors require a fixed liquidity premium of 20 bps. Table A3 also shows that all the main results are robust to controlling for the Pástor and Stambaugh (2003) liquidity risk factor as a benchmark investment. More direct estimates from secondary market trading of syndicated loans find bid-ask spreads of roughly 70 bps, which, when annualized, would imply a liquidity premium of approximately 15 bps. Although some risk-adjusted income may reflect a liquidity premium, it does not seem large enough to explain the 190 bps baseline estimate. In addition to this empirical evidence, theories such as Dang et al. (2017) suggest that banks are willing to pay more (not less) for illiquid assets because it helps with issuing liquid deposits to earn a convenience premium.

1.4 Discussion of Returns & Costs

The risk-adjusted income measures the benefits accruing to the bank net of its systematic risk-taking. However, it does not reflect the resources or costs incurred by the bank or its employees to produce this output. Another interpretation of risk-adjusted income is that it represents the price a borrower is willing to pay to the bank for lending services, including monitoring and information certification, above the risk premium paid to the bank. The paper's main conclusions remain unchanged under this alternative interpretation: there is a market for information production and monitoring with a large positive price, which increases when the bank mitigates more intense financial constraints. The risk-adjusted income measures the employees' labor productivity in mitigating financial constraints, and employees are compensated close to the value of these lending services, indicating their crucial involvement in screening and monitoring services.

1.4 Screening versus Monitoring

The paper's main finding is that banks earn risk-adjusted income by mitigating financial constraints for firms through lending. An important question arising from this finding is how much of the risk-adjusted income is attributable to screening and how much to monitoring. While the paper cannot directly decompose the sources of risk-adjusted returns, I provide some evidence consistent with banks' earning risk-adjusted income from both sources. The lending relationship results in Table 1.4 show that banks earn higher risk-adjusted income when there is a larger information gap between borrower and lender, consistent with the role of information production and screening when banks lend to a firm for the first time. Additionally, in Appendix Table A.11, evidence is provided that banks earn higher risk-adjusted returns when they include stricter earnings-based covenants (Murfin, 2012; Kermani and Ma, 2020) in their loan packages. This is consistent with banks earning more risk-adjusted income when they plan to monitor more intensely.

1.5 Conclusion

Lending is a crucial component of bank activities, yet there is little empirical work analyzing the value of bank lending. This paper estimates the value of bank loans using risk-adjusted returns and documents evidence that banks earn a substantial amount of risk-adjusted returns from their screening and monitoring activities. Banks earn more risk-adjusted income when they address more severe financing frictions of borrowers and expend more resources to overcome more intense informational frictions. In addition to borrowers' need for monitoring, banks' incentives to provide lending services are also an important determinant of banks' risk-adjusted income. Even as banks earn risk-adjusted income by mitigating financial frictions, this also generates some surplus for borrowers. Bank employees capture most of the risk-adjusted income through compensation, which indicates that more theoretical work is needed combining the labor of bank employees and the traditional bank roles of screening and monitoring. This paper provides a new empirical measure and economic framework for analyzing value creation and destruction by banks that can be used in many other empirical settings.

1.6 Tables and Figures

Figure 1.1. Loan Cash-flow Construction

Figure 1.1 shows the basic steps for constructing the loan cashflows. If a loan does not default and is not repaid early, I simply take the scheduled cash-flows from Dealscan as the realized cash-flows. If a loan is prepaid, modified, or defaults, I adjust the scheduled cash-flow accordingly to generate the realized cash-flows.

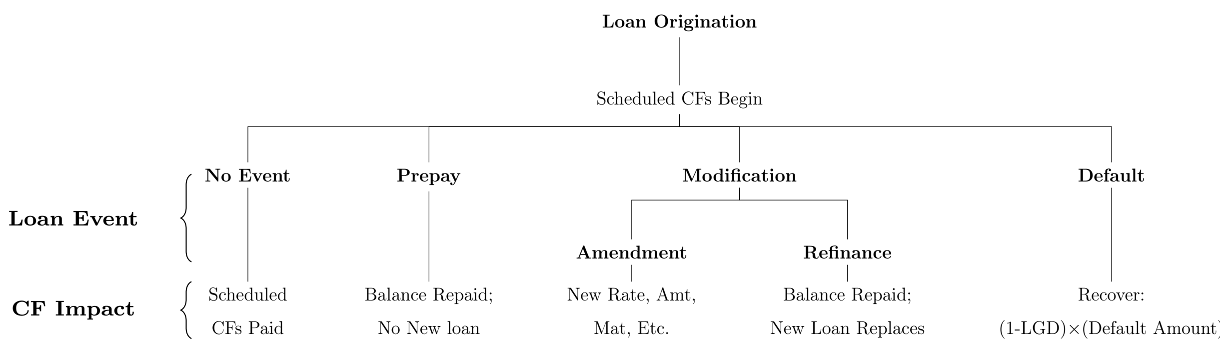

Figure 1.2. Average Loan Cash-flow Distribution

Figure 1.2 plots the quarterly cash-flow distribution of a loan portfolio. The cash-flows distributions are normalized to a $1 investment and averaged across all origination quarters.

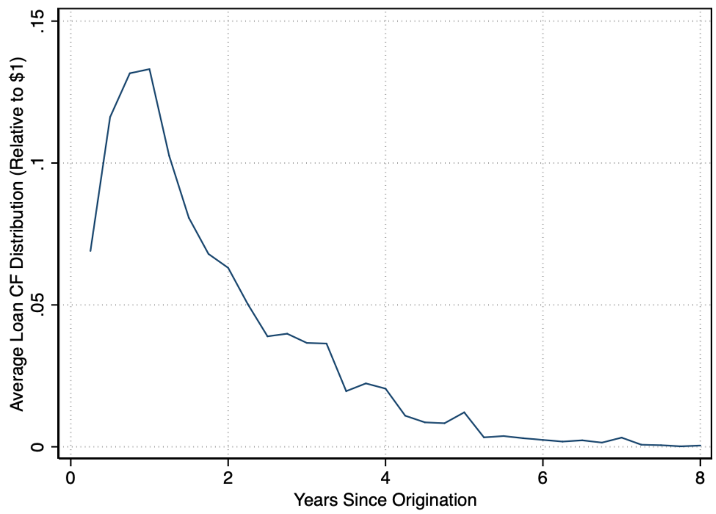

Figure 1.3. Loan Balance Amortization

Figure 1.3 plots the average outstanding loan principal balance by years since origination. The loan principal balance is normalized to a $ 1 investment and averaged across all origination quarters.

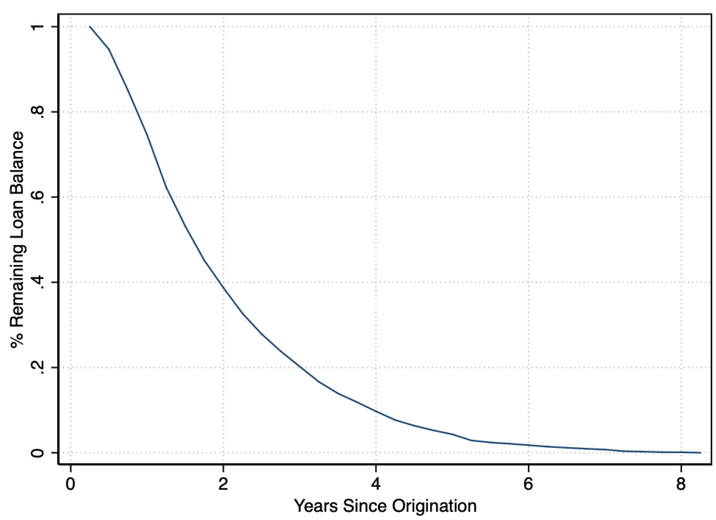

Figure 1.4. Risk Loadings By Horizon

Figure 1.4 plots the risk loadings by cash-flow horizon from the baseline estimates in Table 1.2. 'Zero Coup Bonds' are the coefficients on the yearly horizon fixed effects. The gain investment benchmarks estimated in Equation (1.10) have investment horizon-specific coefficients. 'Corp Bonds' is the sum of the coefficients of the gain investment benchmarks investing in corporate bond securities, including 'Corp Bond', 'DRF Bond', 'CRF Bond' and 'Callable Bond' in the third column of Table 1.2. 'Stock' is the sum of the coefficients of the gain investment benchmarks investing in equity securities, including 'Stock', 'Small', and 'Value' in the third column of Table 1.2.

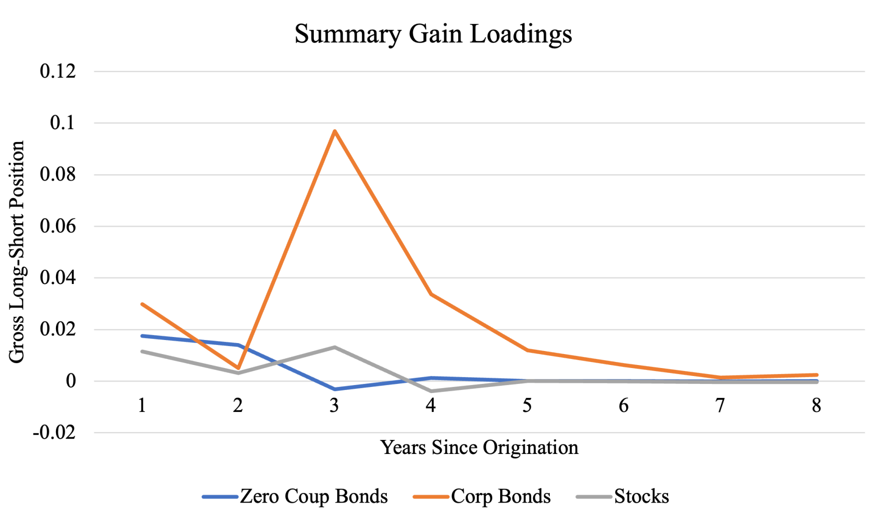

TABLE 1.1. Summary Statistics

Table 1.1 reports summary statistics on the loan sample. 'Loan Amt' is the loan facility amount in millions of dollars. 'Original Mat' is the original loan maturity in years. Refinanced is an indicator equal to one if the loan is prepaid or refinanced before the original maturity. 'Years to Refi' is the number of years since origination that a loan is refinanced. Duration is the weighted average duration of a loan using the cash-flow distributions discounted at the risk-free rate as weights. 'Spread Over 3M tbill' is the loan rate spread over 3M Treasury bill rate at the time of origination. Default is an indicator for whether the loan defaults at any point while it is outstanding. 'Upfront Fee' is the borrower's fee on the loan paid at origination. 'Total Assets' is the borrower's total assets in billions of dollars. Age is the number of years a borrower has been active in Compustat truncated at 37 years. Unrated indicates whether the firm has an unsecured long-term credit rating from S&P. 'Firm Issued Bond' indicates whether the firm has issued a corporate bond in FISD by the loan facility start date. 'Collateral' is an indicator equal to one for whether the loan is secured. 'Cash-Flow Covenant Tightness' is the Murfin (2012) measure of covenant strictness computed for cash-flow covenants. 'Lead Lender Retention' is the fraction of the loan retained by the lead lender.

	Mean	SD	Min	P25	P50	P75	Max	N
Loan Amt.	276	584	1	35	113	300	24000	8152
Original Mat.	4.987	1.678	0.083	4.000	5.000	6.000	8.000	8152
Refinanced	0.849	0.358	0.000	1.000	1.000	1.000	1.000	8152
Years to Refi	1.942	1.272	0.252	0.975	1.597	2.699	7.468	6938
Duration	1.683	1.013	0.223	0.930	1.449	2.293	6.670	8152
Spread Over 3M Tbill	328.727	147.784	33.999	240.250	310.000	383.876	1620.301	8152
Default	0.045	0.206	0.000	0.000	0.000	0.000	1.000	8152
Upfront Fee	69.617	77.103	-50.000	25.000	50.000	89.553	1700.000	8152
Total Assets	3.287	12.817	0.000	0.248	0.779	2.402	466.001	8124
Age	15.210	10.985	2.000	6.000	12.000	22.000	38.000	8152
Unrated	0.470	0.499	0.000	0.000	0.000	1.000	1.000	8152
Firm Issued Bond	0.438	0.496	0.000	0.000	0.000	1.000	1.000	8152
Lead Lender Retention	0.514	0.319	0.000	0.248	0.479	0.769	1.000	7857

TABLE 1.2. Baseline Results

Table 1.2 reports the mean risk-adjusted returns, ψ, and risk loadings from regressing loan portfolio cash-flows on payoffs of loan benchmark funds that invest in public securities. I compute risk-adjusted returns, ψ, by annualizing $\widehat{RAP} = \sum_{h=1}^{H} P^{\$}_{t,h}\hat{a}_{t+h} + \sum_{k=1}^{K}\hat{b^k} - 1$. ψ is reported in percentage points. Observations correspond to the number of loan portfolio cash-flow horizons. Standard errors are computed using the Driessen et al. (2012) non-parametric block bootstrap procedure.

	Bond Factors	Callable Bonds	Stocks + Bonds
Factor Loadings			
Zero-Coupon Bonds			
Zero-Coupon Bond	0.033	0.031	0.030
Rollover Investments			
Floating Bond	0.966	0.965	0.962
Corp Bond	0.076	0.095	0.061
DRF Bond	-0.032	-0.031	-0.032
CRF Bond	-0.006	-0.008	-0.015
Callable Bond		-0.017	0.023
Stock			-0.018
Small			-0.003
Value			0.024
Gain Investments			
Corp Bond	0.213	-0.224	0.004
DRF Bond	0.017	0.005	-0.028
CRF Bond	-0.092	-0.105	-0.084
Callable Bond		0.489	0.296
Stock			0.106
Small			-0.012
Value			-0.071
Number of Loans:	8152	8152	8152
R^2	0.9974	0.9974	0.9975
ψ	2.085***	1.979***	1.908***
	(0.184)	(0.204)	(0.228)

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.3. Value Creation and Financial Constraints

Table 1.3 reports the mean risk-adjusted returns, ψ, for loan portfolios sorted on the financial constraints of borrowers. I form sets of equal-weighted portfolios of loans sorted by the first principal component of the log borrower's total assets (Firm Size), the number of years active in Compustat (Firm Age), whether the firm has a long-term issuer credit rating (Firm Unrated), and whether the firm has issued a corporate bond (Firm Issued Bond). Panel A reports the risk-adjusted returns, ψ, to these portfolios. The first column reports the equal-weighted mean across all portfolios. I estimate risk factor loadings and ψ separately for each set of portfolios, using the 'Stocks + Bonds' model in Table 1.2. 'H-L' reports the mean difference between the high and low constraints portfolios, and 'T-stat' reports the t-statistic for this difference. Panel B reports the mean characteristics of the loans in each portfolio. Standard errors are computed using the Driessen et al. (2012) non-parametric block bootstrap procedure.

	ψ Sorted by Financial Constraints					
Risk-Adjusted Return	Mean	Low	2	3	High	H−
PC1(Constraints)	2.53***	1.75***	2.79***	2.66***	2.91***	1.16***
	(0.10)	(0.20)	(0.21)	(0.21)	(0.29)	(0.36)

	Mean Characteristic Sorted by Financial Constraints					
Measure of Constraints	Mean	Low	2	3	High	H−
Firm Size	3260.87	8967.02	2511.72	1113.82	450.95	-8516.07
	(289.96)	(872.64)	(210.42)	(110.11)	(49.22)	
Firm Age	14.33	22.66	14.25	12.40	8.03	-14.63
	(0.37)	(0.59)	(0.42)	(0.39)	(0.40)	
Firm Unrated	0.48	0.02	0.24	0.68	0.99	0.97
	(0.02)	(0.01)	(0.02)	(0.03)	(0.00)	
Firm Issued Bond	0.43	0.96	0.60	0.16	0.01	-0.95
	(0.02)	(0.01)	(0.03)	(0.02)	(0.00)	

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.4. Value Creation and Lending Relationships

Table 1.4 reports the mean risk-adjusted returns, ψ, on loan portfolios sorted on measures of the lender-borrower relationships. 'Relationship Intensity' is the Bharath et al. (2011) relationship intensity measure. 'Any Relationship' equals one if the borrower has used the lead lender as a lead lender for any previous loan. 'Relationship Length' is the number of years since the borrower initiated a relationship with the lead lender. 'Proximity' is equal to negative one times the number of miles between a lender's headquarters and the borrower's headquarters. Panel A reports the risk-adjusted returns, ψ, to these portfolios. The first column reports the equal-weighted mean across all portfolios. I estimate risk factor loadings and ψ separately for each set of portfolios, using the 'Stocks + Bonds' model in Table 1.2. 'H-L' reports the mean difference between the high and low portfolios, and 'T-stat' reports the t-statistic for this difference. Panel B reports the mean characteristics of the loans in each portfolio. Standard errors are computed using the Driessen et al. (2012) non-parametric block bootstrap procedure.

	ψ by Lender Relationship			
Risk-Adjusted Return	Mean	Low	High	H−
Relationship Intensity	2.48***	2.90***	2.06***	-0.84***
	(0.14)	(0.17)	(0.23)	(0.29)
Any Relationship	2.82***	3.16***	2.49***	-0.67***
	(0.15)	(0.22)	(0.16)	(0.24)
Relationship Length	2.64***	2.95***	2.33***	-0.62**
	(0.15)	(0.18)	(0.22)	(0.28)
Proximity	2.53***	2.99***	2.07***	-0.91***
	(0.15)	(0.15)	(0.25)	(0.28)

	Mean Relationship Char.			
Relationship Measure	Mean	Low	High	H−
Relationship Intensity	0.63	0.36	0.94	0.48
	(0.03)	(0.03)	(0.01)	
Any Relationship	0.50	0.00	1.00	1.00
	(0.04)	(0.00)	(0.00)	
Relationship Length	4.12	1.31	6.94	5.62
	(0.29)	(0.15)	(0.36)	
Proximity	-1333.66	-2195.17	-472.14	1723.03
	(73.99)	(62.81)	(24.86)	

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.5. Value Creation and Syndicate Structure

Table 1.5 reports the mean risk-adjusted returns, ψ, on loan portfolios sorted on measures of the loan syndicate structure. I form sets of equal-weighted portfolios of loans using the lender's loan retention share and the concentration (herfindahl index) of investor holdings in the loans. Panel A reports the risk-adjusted returns, ψ, to these portfolios. The first column reports the equal-weighted mean across all portfolios. I estimate risk factor loadings and ψ separately for each set of portfolios, using the 'Stocks + Bonds' model in Table 1.2. 'H-L' reports the mean difference between the high and low portfolios, and 'T-stat' reports the t-statistic for this difference. Panel B reports the mean characteristics of the loans in each portfolio. Standard errors are computed using the Driessen et al. (2012) non-parametric block bootstrap procedure.

	ψ Sorted by Syn. Structure					
Risk-Adjusted Returns	Mean	Low	2	3	High	H−
Lead Retention Share	2.59***	2.27***	2.35***	2.74***	3.00***	0.73***
	(0.11)	(0.19)	(0.28)	(0.22)	(0.19)	(0.27)
Syndicate Herfindahl	2.64***	1.77***	2.86***	3.12***	2.79***	1.01***
	(0.10)	(0.19)	(0.20)	(0.20)	(0.25)	(0.34)

	Mean Characteristic Sorted by Syn. Stucture					
Measure of Syn. Stucture	Mean	Low	2	3	High	H−
Lead Retention Share	0.54	0.18	0.37	0.64	0.95	0.75
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	
Syndicate Herfindahl	0.39	0.08	0.18	0.44	0.86	0.75
	(0.02)	(0.00)	(0.00)	(0.02)	(0.01)	

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.6. Firm-Lender Matching

Table 1.6 examines the relationship between the lender ownership structure and borrower need for monitoring. The dependent variable is borrower financial constraints measured by the first principal component of the log borrower's total assets (Firm Size), the number of years active in Compustat (Firm Age), whether the firm has a long-term issuer credit rating, and whether the firm has issued a corporate bond. The explanatory variables are syndicate structure characteristics, including the lead lender's balance sheet retention and the concentration index of the syndicate structure. All specifications include time-fixed effects. Standard errors are in parenthesis and are clustered by loan.

	PC1(Constraints)	PC1(Constraints)
Lead Retention Share	1.191***	
	(0.050)	
Syndicate Herfindahl		1.527***
		(0.046)
Constant	-0.583***	-0.527***
	(0.030)	(0.022)
Observations	7831	7831
Time FE	Yes	Yes
R^2	0.178	0.227

Standard errors clustered by loan in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.7. Borrower Value From Loans

Table 1.7 examines how borrowers benefit from receiving a loan and how this value varies with different borrower and loan characteristics. The first panel measures the (-3,3) cumulative abnormal stock return around a loan's announcement date. The second panel measures the change in bond yields around the loan announcement date. The third panel measures loan-bond spreads, which is the difference between the interest rate spread on a loan and a matched bond yield from the closest bond issued in a 120-day window before the start of the loan facility after adjusting the bond yield for the Treasury term structure. 'PC1(Constraints)' is defined in previous tables. Controls in the first panel include the one-year annualized stock volatility of the borrower, and one-year stock return, the firm's total debt to assets at the time of loan origination, the firm's return on assets at the time of loan origination, the log of the facility size of the loan, and the log of the offering amount of the matched bond. All dependent variables are reported in basis points. When indicated, regressions include year-quarter fixed effects. Standard errors are clustered at the loan level.

Stock Reaction to Loan Announcement

	Stock CAR (-3,3)	
PC1(Constraints)		96.19***
		(3.02)
Constant	88.73**	141.6***
	(2.37)	(3.27)
Observations	661	655
Time FE	No	Yes
R^2	0.000	0.175

Bond Reaction to Loan Announcement

	Δ Bond Yield (-3,3)	
PC1(Constraints)		-22.03***
		(-3.81)
Constant	-8.265*	-52.12***
	(-1.94)	(-4.41)
Observations	131	122
Time FE	No	Yes
R^2	0.000	0.480

Loan-Bond Spreads

	Loan-Bond Spreads	
PC1(Constraints)	-46.36***	-43.09**
	(-3.67)	(-2.48)
Constant	-202.5***	-138.1
	(-8.22)	(-0.59)
Observations	549	481
Time FE	Yes	Yes
Controls	No	Yes
R^2	0.357	0.386

Standard errors clustered by loan in parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.8. Estimated Commercial Loan Expense Ratio

Table 1.8 estimates the expense ratios for commercial lending using the hedonic regression approach of Hanson et al. (2015) on FRY-9C banks over 1994 to 2014. Using Equation (1.20), I regress the total non-interest expense of banks on commercial loans, real estate loans, consumer loans, other loans, trading assets, transactions deposits, savings deposits, foreign deposits, and other liabilities, leaving equity and wholesale funding as an omitted category. The expense ratio specific to commercial lending is taken as the predicted value of a bank that only invests in commercial loans using only equity and wholesale funding. Below, I report the estimated total non-interest expense for commercial lending as well as the estimated compensation ratio and other non-compensation expenses of commercial lending. Standard errors are clustered at the bank level.

	Total Non-Interest Expense	Staff Comp.	Non-Comp
$\frac{Expense^{(CI\_Loans)}}{CI\_Loans}$	1.640***	1.088***	0.552***
	(0.194)	(0.125)	(0.097)

Standard errors clustered by bank in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.9. Corporate Bond Placebo Test

Table 1.9 repeats the baseline estimation exercise using a portfolio of corporate bond cash-flows for which the price is known. I compute risk-adjusted returns, ψ, by annualizing $\widehat{RAP} = \sum_{h=1}^{H} P_{t,h}^{\$} \hat{a}_{t+h} + \sum_{k=1}^{K} \hat{b^k} - 1$. ψ is reported in percentage points. Standard errors are computed using the Driessen et al. (2012) non-parametric block bootstrap procedure.

	Bonds Factors	Callable Bonds	Stocks + Bonds
Factor Loadings			
Zero-Coupon Bonds			
Zero Coupon Bond	0.055	0.053	0.044
Rollover Investments			
Fixed Bond	0.981	0.979	1.004
Corp Bond	-0.002	-0.164	-0.359
DRF Bond	0.068	0.072	0.082
CRF Bond	-0.091	-0.101	-0.099
Callable Bond		0.169	0.339
Stock			-0.025
Small			-0.004
Value			0.015
Gain Investments			
Corp Bond	1.289	-0.046	3.223
DRF Bond	-0.192	-0.214	-0.293
CRF Bond	0.629	0.564	0.365
Callable Bond		1.467	-1.555
Stock			0.186
Small			0.230
Value			-0.112
Number of Bonds:	3774	3774	3774
R^2	0.9924	0.9926	0.9933
ψ	0.298***	0.250**	0.074
	(0.111)	(0.113)	(0.118)

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 1.10. Loan Level Analysis with Controls

Table 1.10 estimates loan-level risk-adjusted returns and regresses the estimates on loan sort indicators and loan-level control variables. 'Portfolio Sort' is an indicator variable equal to 1 if the loan is in a high or low category of a loan sort, for which separate risk loadings are separately estimated. The column headers indicate the characteristics on which loans are sorted – for instance, 'Portfolio Sort' for 'Relat Inten.' equals one if the loan is above the median 'Relationship Intensity' and zero otherwise. 'PC1(Constraints)' is a continuous loan-level measure of the first principal component of firm age, firm size, whether a firm has a rating, and whether the firm has issued a corporate bond. Bank Size is the log of the lead bank's total assets. Maturity is the original contractual maturity of the loan. Debt is the ratio of total debt to assets at the time of loan origination. 'Int Cov' is the borrower's interest coverage ratio at the time of origination. Regression standard errors are computed using the Driessen et al. (2012) non-parametric block bootstrap procedure; both risk-exposure estimation and regression are performed within bootstrap.

	Baseline	Relat. Inten.	Proximity	Constraints	Lead Share
	(1)	(2)	(3)	(4)	(5)
Portfolio Sort		-0.840***	-0.574**	1.362***	0.757***
		(0.295)	(0.273)	(0.391)	(0.293)
PC1(Constraints)		0.393***	0.315***		0.339**
		(0.115)	(0.0773)		(0.136)
Log(Loan Size)		0.225**	0.125	0.245**	0.283**
		(0.110)	(0.0881)	(0.103)	(0.132)
Maturity		-0.00118	0.00159	-0.0119**	0.00387
		(0.00567)	(0.00468)	(0.00600)	(0.00801)
Bank Size		0.609***	0.651***	0.161	0.648***
		(0.159)	(0.151)	(0.262)	(0.171)
Debt		0.0120	0.0101	0.0212	-0.759
		(0.367)	(0.457)	(0.564)	(0.532)
Int Cov		0.00292*	0.00122	-0.000893	-0.000831***
		(0.00151)	(0.00178)	(0.00168)	(0.000322)
Constant	1.500***	-2.656	-1.103	-3.043*	-1.103
	(0.123)	(1.877)	(1.435)	(1.755)	(2.175)

Bootstrapped standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Chapter 2: Did Banks Pay Fair Returns to Taxpayers on TARP?

This chapter coauthored with Amiyatosh Purnanandam of the Ross School of Business, University of Michigan,

2.1 Introduction

Banking crises are fairly common around the world. Laeven and Valencia (2008) identify 124 episodes of systemic banking crises across the world from 1970 to 2007. They also show that governments frequently respond to these crises by providing financial support, including the injection of fresh capital into the banking sector. How large a subsidy, if any, do banks receive through these interventions? How does the implementation of these interventions affect the extent of the subsidy? Despite the usefulness of these questions for the design of future bailouts, there is limited empirical research on the measurement of bailout subsidies on a risk-adjusted basis. We propose a simple model-free framework to do so using an attractive empirical setting: capital injections by the U.S. Treasury under the Troubled Asset Relief Program (TARP) in 2008-2009. We compute the subsidy as the difference between the realized return to the taxpayers on TARP and a "fair" return that is measured as the return that a private investor would require to hold securities with similar risk for the same time period.

A clear assessment of the TARP's financial cost is also important for informing policy-makers and the public.[1] While the academic literature makes a clear distinction between the

[1] Public opinion plays an important role in designing and implementing banking policies, especially the ones related to bank failure and bailouts. For example, Brown and Dinc (2005) show that political concerns play a major role in government interventions in distressed banks. Agarwal et al. (2014) document the importance of regulator's incentives on the implementation of identical policy rules.

paper versus economic profit of an investment, bankers and some market observers often stress the fact that TARP recipients paid the taxpayers back with profits, without making a clear distinction between the two.[2] The fact that these investments were paid back with positive returns has been used as an argument in favor of ex-post renegotiation of TARP contract terms, including early repayment and repurchase of warrants by the recipients, and broader policy changes in the banking sector after the recovery from the financial crisis. Such a narrative misses a critical aspect of finance theory that the fair return on an investment must compensate for the underlying risk of the security. Because TARP investments were made in a bad state of the world, a lack of risk-adjustment can lead to a substantial underestimation of the subsidy.

We focus on a specific part of the TARP intervention: the Capital Purchase Plan (CPP), where the Treasury invested $205 billion in financial institutions through preferred equity with warrants. We observe the exact dates and amounts of CPP investments as well as their repayments, including the cash flows received from the exercise of the warrants. We compute the internal rate of return (IRR) of these cashflows for each recipient and label it as the "TARP's return". We compare TARP's return to carefully selected benchmarks on other securities with comparable risk to estimate the extent of subsidy.

Preferred equity issued under the TARP had the same seniority as the existing preferred equity of the recipient banks. Thus market-based returns on the existing preferred equity of the same bank over exactly the same time horizon provide close to an ideal benchmark. Our approach obviates the need to rely on an explicit asset pricing model: we simply compare returns on two securities with similar risk issued by the same firm over the same time horizon. While not all TARP recipients had actively traded preferred equity outstanding at the time of TARP investment, 20 of the largest recipients covering about 80% of total investments made under the plan did. TARP recipients paid 11% annualized returns to the taxpayers compared to the benchmark's annualized return of 39% over exactly the same time horizon. On a

[2]For example, see "U.S. ends TARP with $15.3 billion profit" at https://money.cnn.com/2014/12/19/news/companies/government-bailouts-end/. Similarly, Wells Fargo's CEO John Stumpf stated that TARP's "success also generated financial returns for taxpayers, including $1.4 billion in dividends paid to the U.S. Treasury by Wells Fargo."

bank-by-bank basis, 19 of the 20 TARP recipients paid lower returns than the benchmark. Our next benchmark is an index of preferred equity instruments issued by S&P 500 firms.[3] We are able to compute the subsidy for the entire sample of banks using this benchmark. On the value weighted basis, TARP's return was 9% per annum compared to 39% for the benchmark. These estimates translate into a subsidy of $54 billion on the aggregate basis.

One may be concerned that preferred equity invested under TARP came with warrants, whereas our benchmark securities are plain preferred equity. Since warrants are riskier than preferred equity, the return on plain preferred equity provides a conservative estimate for the cost of capital of TARP (e.g., Coval and Shumway (2001)). Further, the presence of warrants is unlikely to make a significant difference in the risk of these claims because ex-ante valuation estimates suggest that the warrants represented only about 8-10% of the value of the entire investments (see Veronesi and Zingales (2010)). Still, we directly address this issue by creating a synthetic benchmark that replicates the returns to a portfolio that invests 90% in the preferred equity of the bank and 10% in an American Call Option that closely mimics the value of warrants based on the TARP's terms. Our results remain similar.

We also consider as a benchmark the return earned by a large private investor, Warren Buffett, on his investment in Goldman Sachs during the financial crisis. Although the Buffett deal had the same security design, namely, preferred equity with warrants, it had a much higher coupon rate (10% against the CPP's rate of 5%), a prepayment penalty, and a significantly higher number of warrants attached to it. Compared to this benchmark, the TARP's return was even lower: 50% lower on an annualized basis.

In the next part of the paper, we focus on the ex-post renegotiation of TARP contract terms. As per the original terms of TARP, preferred equity could not be paid back before a maturity of three years, and the warrants had a maturity of 10 years. However, banks actively renegotiated these terms soon after the economy began to recover. On average, preferred equity investments were repaid almost a year earlier than the three year maturity initially

[3]Though we miss bank-specific variation in returns in this benchmark, it is still an attractive benchmark for the TARP investment because about 70% of issuers in this index are financial institutions, and during the sample period, time-series variation in return dominates differences in returns across banks.

agreed upon. Subsequently, the warrants were either repurchased by the issuing bank at a model-based valuation or sold in an auction.

The renegotiated terms had the potential to lower taxpayer returns both through unattractive repayment terms of the preferred equity and lower valuation of the warrants. Based on prevailing market prices, the yield on comparable preferred equity at the time of the TARP prepayment was about 4%, i.e., lower than the 5% coupon rate on TARP securities. Since prepayments were made at par value, early repayment amounted to a subsidy of approximately $2 billion, or equivalently about 1% of the investment amount.

To calculate the effect of warrant disposal, we take a model-free approach since the estimation of forward volatility on long-dated securities is highly sensitive to modeling assumptions. Specifically, we analyze how the recipient banks' stock prices reacted to the news of warrant disposition on two important dates: (a) the announcement on June 26, 2009 by the Treasury detailing its framework to repurchase warrants, and (b) the date on which a bank received the approval for the disposal of warrants which varied by the bank. Consistent with the view that warrant repurchase was beneficial to banks, their stock price experienced a +1.7% cumulative abnormal return in a three day window surrounding the Treasury's announcement of the framework. Since warrants were either sold in the market based on an auction or repurchased by the bailed-out institutions at a negotiated price, we are able to tease out the impact of renegotiation more carefully. The repurchased warrants represent successful renegotiation by the banks, whereas the sold ones do not. Banks that repurchased their warrants experienced significantly higher (+1.9%) stock price reactions in a three-day window surrounding the warrant disposal date compared to banks whose warrants were sold in the market.

Although a detailed analysis of the causal effects of renegotiation on gains to shareholders and managers is beyond the scope of our paper, we do provide some suggestive evidence on this front in the last part of the paper. We show that banks with larger subsidies increased their dividend payments soon after the repayment, and bank CEOs gained significantly in terms of their total compensation. Further, CEOs who were able to successfully repurchase warrants from the Treasury earned significantly higher compensation than CEOs of banks whose warrants were sold in an auction. In conclusion, we show that taxpayers received considerably lower returns, whereas shareholders and managers benefitted from TARP. Further, gains from recovery were not shared with the taxpayers in the same amount as originally promised.

A key limitation of our work is that we do not comment on the welfare effects of the TARP bailout. Our measurement of TARP subsidies, however, is an essential step in any such welfare calculation. In the context of a Bagehot style intervention, our exercise shows that the contract terms were not set at a "penalty" rate compared to the market rate of alternative sources of funds, for example, the terms on the Warren Buffett deal. However, one might argue that the terms of CPP securities were at a penalty rate compared to the return on preferred equity instruments in normal times. In the end, the determination of contract terms should depend on the extent of subsidy the regulators are willing to pass to the financial sector. Our analysis provides a benchmark for calculating such a subsidy.

Our results have immediate implications for the disclosure and computation of bailout subsidies, the design of future bailouts, and theoretical models of security design. The Congressional Budget Office (CBO) is tasked with calculating the financial performance of TARP investments. They use realized gains and losses on these instruments and use the risk-free rate to compute their net present value. As per their estimate, CPP resulted in a net gain of \$16 billion, whereas our estimates show a subsidy of over \$50 billion.[4]

Our results show that the implementation of bailouts must account for the opportunity cost of penalty-free prepayment and warrant renegotiations. Taxpayers are likely to earn a higher return if the prepayment of investment in the good state of the world comes with a penalty. Further, their returns are likely to be higher if warrants are sold in an auction rather than repurchased at a model determined price. While the economic rationale for financial assistance at the time of crisis is clear, there is no clear economic reasoning for providing banks with a subsidy once financial markets have recovered. Minimizing ex post subsidies to banks should be an important component of any future bailout package.

A suitably designed security for bailouts, as in the theoretical model of Philippon and

[4]The report is available at https://www.cbo.gov/publication/57341

Schnabl (2013), requires the participating banks to share their upside gains with the government in good times, for example, through adequately priced warrants. Our findings show that even though the securities were designed as such, ex post renegotiation limited the taxpayers' upside gains. Further, Bianchi (2016) and Dávila and Walther (2020) show that the possibility of a bailout changes the ex-ante leverage or risk-taking incentives of banks. Since highly levered and riskier banks are more likely to do better in good times, their warrants are more likely to have higher value when the economy recovers. Therefore taxpayers may be at a severe disadvantage if these warrants are renegotiated in good times: highly levered institutions are likely to get higher subsidies at the time of the bailout and the leverage gain is not shared with the taxpayers in the upside. Therefore, future theoretical models of bailout design must take seriously into account the government's commitment not to renegotiate these contracts, and the renegotiation-proofness of bailout design in general (Hart and Moore, 1988; Bolton, 1990). Even if such a contract cannot be written, our results show that reliance on a market-based mechanism for the ex post disposition of securities can significantly limit the cost to the taxpayers.

Our work can be extended in a number of directions. Did banks with higher subsidies engage in riskier activities? Did it affect their credit supply? Did politically connected banks get better terms in line with the results of earlier literature on political connections (e.g., Duchin and Sosyura (2012); Akey (2015))? Similarly, our framework can be extended in international settings to study the political, legal, and economic drivers of bailout subsidies across the world (Brown and Dinc, 2005). Since our work investigates just one type of bailout design, a limitation of our work is that we cannot comment on the relative costs and benefits of alternative bailout designs such as debt-for-equity swaps or asset purchases. But our framework can be a reasonable starting point for comparing the financial cost of bailouts across countries with different elements of design. Our study can also be extended to better understand the incentives and constraints of regulators in implementing a bailout package (Agarwal et al., 2014).

There is a large academic literature on TARP covered in survey papers such as Berger and Roman (2020) and Calomiris and Khan (2015). However, there is no previous work that has analyzed the returns on TARP securities compared to market benchmarks, and the effect of renegotiations on these returns. We discuss the connection between our work and the prior literature in detail in the next section.

2.2 TARP Details & Literature Review

TARP was one of the key interventions undertaken by the U.S. Treasury to stabilize the U.S. financial firms after the collapse of Lehman Brothers in September 2008.[5] Within the overarching umbrella of TARP, there were several specific programs such as Capital Purchase Program (CPP), Asset Guarantee Program (AGP), Auto-sector bailout, and investment in AIG. Our focus in this paper is on the Capital Purchase Program (CPP) that injected capital into the banking system in the immediate aftermath of the crisis.

Under the CPP, the U.S. Treasury invested $205 billion in about 700 financial institutions of the country. Most investments happened in the last quarter of 2008, but they continued in the early parts of 2009 as well. These investments were structured as preferred equity with warrants that gave the Treasury an option to buy common equity of the firms anytime in the future up to ten years after the investment date. The coupon rate was set at 5% per annum for the first five years of investment, and 9% thereafter. Warrants allowed the Treasury to purchase common shares equal in cost to 15% of the amount invested at a strike price set at the average of the institution's common stock price over the 20 trading days preceding the date of investment.[6]

The preferred equity was perpetual in nature, with a condition that it could not be redeemed before a period of three years. However, the American Recovery and Reinvestment Act of 2009 (ARRA) amended TARP to allow for early repayment of the preferred equity investment subject to Federal approval. Following the change, in June 2009 the Federal Reserve laid out criteria under which banks could repay TARP before the original maturity

[5] https://www.treasury.gov/initiatives/financial-stability/about-tarp/Pages/default.aspx

[6] Naturally, the arrangement to buy common shares based on the average share price of the bank was only applicable to publicly traded institutions. These institutions received over 97% of the amount invested under the CPP.

date.[7] Of the $205 billion in CPP investments, 90% of the principal was repaid before the original maturity. Soon after the repayment of preferred equity, outstanding warrants were disposed of by the Treasury for a vast majority of banks.

There is a vast literature on TARP, covered comprehensively in Berger and Roman (2020) and Calomiris and Khan (2015). Berger and Roman (2015), Li (2013), Bayazitova and Shivdasani (2012), Black and Hazelwood (2013), Duchin and Sosyura (2014), Chavaz and Rose (2019), and Berger et al. (2020), among others, study the effect of TARP on outcomes such as credit supply, bank competition, and risk-taking. Veronesi and Zingales (2010) and Glasserman and Wang (2011) focus on the valuation of TARP instruments and bank shareholders.

Our study complements Veronesi and Zingales (2010) who analyzes changes in the value of the financial claims of the ten largest recipients of TARP around the announcement date of the CPP program. Our work is conceptually related to Lucas (2019) who advocates the use of state contingent pricing in computing the fair value of bailout assistance. Our findings are also related to Wilson (2009) who shows that the TARP warrants were undervalued when Old National Bancorp, the first publicly traded company to do so, repurchased it from the Treasury. Unlike their studies, we focus on ex-post realized returns of preferred equity based on actual repayments.[8] This allows us to shed light on risk-return trade-off for TARP investments and directly assess whether the recipients enjoyed a subsidy or not in a model-free approach using the ex-post cash flows after accounting for the renegotiated terms. These findings have not been documented before to the best of our knowledge. Finally, our study also relates to the literature on the role of government support to the banking sector such as Atkeson et al. (2019) and Gandhi and Lustig (2015). The subsidy enjoyed by the

[7]As stated in the Department of Treasury's Warrant Disposal Report dated December 31, 2012 "Originally, the CPP contracts provided that an institution could not redeem the investment within the first three years except with the proceeds of a "qualified equity offering" (QEO), which is an offering of securities that would qualify as Tier 1 capital. The repayment terms of the contracts were later effectively amended by the ARRA, which provides that an institution can repay from any source of funds and without regard to any waiting period."

[8]For instance, the preferred equity valuation in Veronesi and Zingales (2010) assumes that preferred equity was fully repaid after five years. Ex-post, this was renegotiated and the largest banks repaid the preferred equity in less than two years.

shareholders of the bank in bad times can be an important driver of bank valuation and returns in good times.

2.3 Our Framework

A key feature of the CPP investment is that they were made at a time of great distress in the overall economy and specifically in the financial sector. U.S. banks' equity return dropped by almost 25% between January 1, 2008 to September 20, 2008, right after the collapse of Lehman Brothers. Bank's default risk increased by a significant amount as evidenced by an increase of 312% in their CDS spreads (see Figure 2.1). The short-term debt market froze due to disruptions in the money market mutual funds (see Kacperczyk and Schnabl (2010)). Overall, this was an extremely bad state of the world, and private investors were reluctant to provide capital to the banking sector. Thus, at a time like this the required rate of return from a market participant's perspective is likely to be high to compensate them for the additional risk they are taking (see Figure 2.2).

[See Figure 2.1]

[See Figure 2.2]

We measure "fair" return on TARP investments as the rate of return that a replicating portfolio in financial markets would earn. Thus, our study analyzes whether the recipients paid the Treasury the same rate that they would have paid for raising similar funds from the private markets on the same day. The following timeline presents the dates of key events during this period.

[See Figure 2.3]

In the immediate aftermath of the failure of Lehman Brothers in September 2008, there was considerable uncertainty about the policy intervention as well as the precise nature of the policy (e.g., asset purchase versus equity injection in banks, see Calomiris and Khan (2015)). Eventually, on October 13, 2008, the CPP announcement was made public, and it became clear that the Treasury would invest in financial firms using preferred equity. Actual investment began two weeks later when the top nine banks of the country received CPP investments on October 28, 2008. A number of other institutions received funds in the subsequent weeks and months. These funds were repaid back, on average, in the first quarter of 2011 as against the original earliest repayment date of the first quarter of 2012. We measure returns from the date of investment (e.g., October 28, 2008 in the timeline above) to the date of actual repayment (indicated by 2011Q1 in the timeline above). The actual investment date and repayment date vary for each bank depending on their exact dates of receiving the funds and paying them back.

Using the Treasury's dataset on TARP, we obtain daily cashflows from every TARP investment, including investment, dividends, principal repayments, and warrant proceeds. TARP return for each bank is computed simply as the annualized internal rate of return that sets the NPV of these cashflows to zero. Benchmark returns are calculated as the annualized rate of return from investing in the respective market benchmark using exactly the same investment horizon, i.e., from the date of investment to the repayment of each bank's TARP investment. Appendix F.XXI. provides an example of this computation using investment in JP Morgan Chase as an example.[9]

Between September 15 and October 13, labeled as the "policy uncertainty" period on the timeline, private markets faced uncertainty about the policy intervention itself. A part of the subsidy that banks enjoyed came from the effect of policy intervention on the security prices after the announcement of CPP on October 13. The other part comes from receiving cheaper funds from the Treasury conditional on the survival of the entire financial system. As the timeline shows, our benchmark returns begin two weeks after the policy announcement. During the "CPP Ann Period" (Oct 13 – Oct 28), market prices had sufficient time to adjust to the news of policy intervention. If the policy announcement itself resolves the uncertainty about the aggregate stability of the system (e.g., Roch and Uhlig (2018)), then our measure captures the subsidy solely due to the differential pricing of the standard risk conditional on

[9]Some banks received TARP investments on two different dates. For such banks, we compute a value weighted portfolio return proportional to the investment amounts.

the resolution of uncertainty about the financial stability of the entire sector. As Veronesi and Zingales (2010) show, market prices indeed reacted considerably to the announcement of CPP right after October 13. Consistent with their findings, bank CDS spread dropped from 512 basis points to 309 basis points during the "CPP Ann Period" (see Figure 2.1).

It can be argued that some uncertainty about policy interventions remained even after October 28. In that case, our measure of subsidy does include some effects of policy uncertainty as well. We do not separate these two parts of the subsidy. But in an additional test, we compare TARP returns with return on private market securities only in periods when there was no longer any uncertainty about the aggregate stability of the financial sector. Specifically, we compare TARP investment's return with the return on private market securities shifted by a period of six months to one year.

2.3 Limitations of Our Framework

Our framework has certain limitations. First, we do not measure welfare gains from TARP. Therefore, our measure of subsidy is specific to financial gains and losses alone. Second, there may be a concern about the lack of liquidity in the private market benchmarks that we use for the calculation of fair returns. And third, while our benchmark return for the preferred equity part is direct, for the warrant portion of the benchmark return we do need to rely on a model. We address issues regarding the lack of liquidity and the need for a warrant valuation model later in the paper after we present our main results. In general, we show that the economic magnitude of these limitations is not large enough to overturn the key message and calculation of our paper. Finally, our study computes subsidy without considering the endogeneity concern that the benchmark return in the private market may itself depend on the extent and nature of government intervention. In this sense, our estimate is "marginal" in nature, i.e., it computes subsidy on the marginal taxpayer dollar conditional on the government's desire to intervene.

2.4 Data

We collect data from several sources. Information on TARP investments and repayment comes from the Department of Treasury's website.[10] This dataset provides bank-level information on the size, timing, and repayment of CPP investments including dividends and warrant proceeds. We limit the sample to banks receiving preferred equity investments, which make up over 99% of the total CPP investment amount.[11] We obtain information on warrant disposition, i.e., sales and auctions, from the Treasury's website as well.[12]

We obtain information on preferred equity benchmarks from two sources: Mergent FISD and Refinitiv Datastream. Mergent FISD provides information on the characteristics of preferred equity issued by the recipient banks. From this dataset, we take the most recent preferred equity issued prior to 2008 with pricing data available until the end of the original TARP maturity for our benchmark returns. Refinitiv Datastream provides information on returns. For the bond benchmark, we obtain data from Bond CRSP Link provided by WRDS.[13] Bond returns are calculated using information on bond coupons from the FISD and market prices from the TRACE datasets following the methodology in Bai et al. (2019).[14]

We obtain bank-level common equity returns from CRSP. We use the Bank CRSP-Compustat merged dataset to obtain data on dividends and share repurchases.[15] Executive compensation data comes from Execucomp. Using the Fed NY link file, we link banks in CRSP to Bank Holding Company from the Call Reports for bank characteristics. We

[10] Available for download at https://www.treasury.gov/initiatives/financial-stability/reports/Pages/TARP-Investment-Program-Transaction-Reports.aspx

[11] Some smaller banks received subordinated debt investments. We exclude these investments from our analysis to maintain uniformity in benchmarks and comparison of TARP subsidy across banks.

[12] Available at https://www.treasury.gov/initiatives/financial-stability/reports/Pages/Warrant-Disposition-Reports.aspx

[13] We consider bonds issued before the CPP investment date and maturing after the redemption date. We also impose standard filters used in the corporate bond literature on the sample. Specifically, we restrict the sample to senior bonds, corporate debentures and medium-term notes, bonds with $1000 principal amount, bonds with non-changing coupon, and bonds with greater than $50,000,000 offering amount.

[14] Bond returns are computed at the monthly frequency due to limited daily trading. We convert monthly returns to daily returns when calculating the returns over a given TARP investment horizon. Returns on preferred equity benchmarks are available on a daily basis.

[15] A few banks in CRSP received multiple TARP investments. For these banks, we keep the largest Treasury investment for analysis requiring CRSP data.

measure bank characteristics on 2009Q1, the average initial investment time of TARP CPP investments. Finally, we obtain information on the implied volatility of the longest dated option of the recipient banks using the OptionMetric database.

Table A.12 in the online Appendix provides further details on the sample used in our analysis. We start with all 707 banks that received an investment from the TARP's CPP program. Of these banks, 653 received preferred equity investments. We have individual preferred equity returns for 20 banks. Finally, we obtain individual senior bank bond returns for 21 banks, 17 of which overlap with the preferred equity subsample. While the samples requiring returns on individual bank preferred equity or bonds are much smaller, they both account for almost 80% of the CPP investment in terms of dollar value.

2.4 Descriptive Statistics

Table 2.1 provides key summary statistics of TARP investments and bank characteristics. As shown in the table, the average bank received an amount of $312.9 million under the CPP. The earliest TARP investment was made in October, 2008 and the median investment date was January 2009. While the average effective maturity of the investments was just over three years, about half of the 653 banks repaid the principal investment before the original maturity. Larger recipients paid it back much earlier. On a value weighted basis the effective maturity was 1.7 years.

[See Table 2.1]

2.5 Results

We present our estimates of TARP's risk-adjusted realized return for various benchmarks in this section of the paper.

2.5 Estimation of Benchmark Returns

2.5 Same bank preferred equity return:

Preferred equity issued under the CPP had the same seniority in the bank's capital structure as the existing preferred equity of the bank.[16] Thus, the closest market based benchmark comes from the traded preferred equity of the same bank outstanding at the time of CPP's investment. This benchmark captures both the timing of the TARP investment horizon as well as the (time-varying) risk characteristics specific to the bank receiving the investment.

We are able to get this data for 20 banks in our sample, representing 78% of total CPP investment. The data on the total return of these instruments are available at the daily frequency, allowing us to compute the benchmark return for exactly the same time horizon as the CPP investment. Panel A of Table 2.2 provides the estimation results. Individual preferred equity holders earned a value-weighted annualized return of 40% compared to the 11% earned by TARP.[17] The equal-weighted results are similar with a preferred equity return of 49% compared to 10% earned by TARP. Both differences are statistically significant at the 1% level. Figure 2.4 presents bank-by-bank return on TARP investment and the bank's individual preferred equity. The difference in TARP return and preferred equity return is stark: of 20 banks, TARP earned considerably lower returns than preferred equity holders in 19 cases.

[See Table 2.2]

[See Figure 2.4]

[16]As quoted in the congressional oversight panel report dated July 10, 2009 "The CPP preferred shares .... are senior to the institution's common shares, have an equal preference to existing preferred shares, and are non-voting."

[17]All the value weighted returns are computed with the original investment amount as the weight.

2.5 S&P US preferred equity index return:

A limitation of the same bank preferred equity benchmark is that it is not available for most firms. We use the return on S&P US Preferred Stock Index as an alternative benchmark to estimate the subsidy for the entire cross-section of banks. This index is designed as an "investable benchmark representing the U.S. preferred stock market". The bulk of the index constituents, 70%, are from the financial sector. For instance, the top 10 constituents include preferred shares from Citigroup, Ally Bank, JP Morgan Chase, Wells Fargo, and PNC Financial. The return on this index closely mimics the value-weighted return on preferred stocks for 20 banks we use for the bank-level analysis. The two return series have a positive correlation of 95%. Hence the index return provides a useful benchmark for banks without traded preferred shares.

Panel B of Table 2.2 provides the estimation results. TARP's equal weighted annualized return for the entire sample is -1%, i.e., on average a bank in the sample returned less money than it received from TARP. However, the value-weighted return to the TARP investment is 9% per annum, which is very similar to the estimate based on the sample of 20 banks discussed above. Over the same time period, the S&P U.S. Preferred Stock Index earned a much higher average annualized return of 39%. Thus, TARP's return is almost one-fourth of a comparable market investment. The subsidy of 30% is statistically significant at 1% level.[18]

2.5 Replicating portfolio return:

A shortcoming of the preferred equity return benchmarks is that we miss the warrant portion of the investment from the benchmark return. These warrants are American Call Options on the recipient bank's common stock. As such, they are riskier claims than both the common stock and preferred equity of the bank. Hence, the omission of warrant makes

[18] One potential concern with comparing TARP returns and the traded preferred equity returns is that these instruments might be exposed differently to duration risk. This feature is unlikely to be a significant issue for our results since ex-ante TARP investments had perpetual maturity, whereas traded preferred equity has an average duration of over 40 years. As discussed earlier, TARP recipients had the option to repay the investment after three years. In reality, however, they paid it even sooner. In Appendix F.XXIII., we examine how the subsidy changes if we account for the differences in duration assuming TARP investment has a shorter duration based on actual repayment. Our results become slightly stronger.

these benchmarks less risky and therefore biases against our finding.

To directly address this issue, our third benchmark replicates returns on a portfolio of preferred equity and warrants that closely mimics the value of TARP warrants. We closely follow the Treasury's methodology in valuing these warrants as an American Call Option on a dividend paying stock using a binomial approximation of Black-Scholes valuation model.[19] Using these model-implied, values we compute the return to the warrant portion of the portfolio over the investment horizon. The replicating portfolio assigns a weight of 90% on the preferred equity claims and 10% on warrants, in line with the ex-ante valuation estimates of Veronesi and Zingales (2010). Appendix F.XXIV. provides further details on warrant valuation methodology and assumptions underlying the inputs to the model.

Panel C of the Table presents the results.[20] The results are almost identical to the results presented with straight preferred equity as the benchmark. This is not surprising because the portfolio has 90% weight on straight preferred equity and only 10% on warrants.

2.5 Buffett's investment in Goldman Sachs:

Warren Buffett invested $5 billion in Goldman Sachs soon after the failure of Lehman Brothers using the same security design as the TARP investment: preferred equity with attached warrants. However, the terms of his investment were considerably different. The Buffett deal had a 10% coupon as against 5% for TARP, it had a prepayment penalty of 10% of the invested amount as against none for TARP, and it came with a significantly higher number of warrants. Specifically, the Buffett deal gave his firm an option to buy common shares worth $5 billion on the date of investment (i.e., 100% of the investment amount). The corresponding amount of common shares for TARP was set at 15% of the invested amount. This deal from a private market investor provides us with an attractive benchmark since it closely matches the timing of the investment as well as the design of the security. Further,

[19] Although TARP recipient banks had dividend restrictions during the repayment period, these restrictions limited *increases* in dividends not the level of dividends.

[20] We present this analysis for 19 banks for which we have preferred equity returns as well as actively traded options in the market. We do so because we need option-implied volatility for the estimation of the warrant valuation model.

this benchmark is free from any liquidity-related issues that may contaminate our findings based on returns from the market instruments. We compute the benchmark return for each bank under the condition that they all received the same terms as the Buffett deal. Panel D presents the results. For this benchmarking, the subsidy is even higher at 50% per annum on a value weighted basis.

The overall message from our benchmarking analysis is clear: taxpayers received at least 30% lower returns on an annualized basis compared to securities of similar risk.

2.5 Same bank senior bond return:

Our next benchmark is constructed to capture a lower bound on preferred equity returns: the senior bond returns of the same bank. We have data on bond returns for 21 banks in the sample – these 21 banks account for 80% of the CPP's $205 billion investment. Panel E of Table 2.2 shows that the bank's bondholders earned an equal weighted annualized return of 19% compared to the 12% earned by TARP. On the value weighted basis, the results are similar: 20% versus 12%. Thus, the taxpayers earned almost one-half the return earned by senior claim-holder in the same firm.

Our benchmarking analysis is based on realized returns. Junior claims are expected to earn higher returns than senior claims on average, but not in every sampling period. However, this does not pose any problem for our analysis since we are analyzing the return differential across the junior and senior claims in a setting when the investment was made in a very bad state of the world, and the return was realized in the good state of the world. For such an investment horizon, the realized return on a junior claim should be especially higher. But that was not the case for TARP investments.

Table A.14 in the Online Appendix uses two bond indices as the benchmark return: (a) Bloomberg Barclays Investment Grade Bond Financial Institution, and (b) Bloomberg Barclays BBB Bond Index. The advantage of this benchmark is that we are able to compare the returns for the entire sample of financial institutions, and not only the banks that have issued bonds. The results are similar.

2.5 Dollar value of subsidy & Cross-sectional drivers:

We estimate the dollar gains or losses on TARP investments by computing their NPVs. We do so by discounting the TARP cashflows at a rate that equals the benchmark returns calculated earlier. Results are presented in Table 2.3. Panel A calculates NPV for the entire sample of banks using the cumulative return on S&P US Preferred Stock Index return over the investment period as the discount rate. Panel B repeats the exercise for the smaller subsample of 20 banks, with the bank's own preferred equity return as the discount rate. As shown in Panel A, the average 'Dollar NPV' of TARP is negative $83 million, meaning TARP investments lost an average of $83 million across 653 banks. This puts the total dollar cost of subsidy at roughly $54 billion on an investment amount of $205 billion. Panel B of Table 2.3 presents results for the sample of banks that have traded preferred equity. The results are similar.

[See Table 2.3]

The table also reports NPV per dollar of TARP investment. On average a $1 investment in TARP lost 43.5 cents. From the bank's perspective, NPV per dollar of bank asset works out to -0.009, which means that the economic subsidy amounted to 0.9% of the bank's assets on average, which is a significant amount when compared with the average return on assets in the banking industry.[21]

We also investigate whether the cross-sectional variation in subsidy is related to individual banks' risk as measured by beta, historical volatility, and size. Unsurprisingly, riskier banks received economically larger subsidies from TARP since the terms of investment did not change with the recipient's risk. These results are reported in the online Table A.13.

2.5 Renegotiation of TARP Contracts

CPP investments were renegotiated between the U.S. Treasury and the recipients soon after the financial markets began to recover. The renegotiations involved shortening of maturity

[21] For example, the average quarterly return on assets for FDIC-insured institutions was 0.88% in 2011Q4. See https://www.fdic.gov/bank/statistical/stats/2020dec/fdic.pdf

as well as repurchases of warrants by the issuers. Early repayment allowed banks to pay back the preferred equity principal at par value after yields had fallen significantly since the peak of the crisis. The original contract stipulated that banks could only repurchase warrants after at least three years of the repayment of the preferred equity principal. Renegotiation also enabled early warrant repurchase. As a result, many banks began repurchasing warrants from the Treasury starting in July 2009 after the early repayment of the preferred equity principal.[22]

Table 2.4 contains descriptive statistics on the renegotiation of TARP contracts. 304 out of 653 financial institutions in our sample repaid TARP earlier than the original three year term. On a value-weighted basis, 90% of TARP investment was renegotiated. On warrants, about 97% of investments on value-weighted basis came with warrants attached to them. The Treasury's warrant disposition report provides information on 95% of warrant investments, including information on how the Treasury disposed of the warrants. On a dollar-basis, about half the warrants were repurchased by the banks while the other half was sold to market participants. We compute the effect of these renegotiations on TARP returns and present the results below.

[See Table 2.4]

2.5 Early Repayment Subsidy

The early repayment renegotiation allowed banks to repay instruments with 5% coupon without any prepayment penalty when yields on comparable securities had come down. Between the time of TARP investment and repayments, the risk-free rate declined by a significant amount, the banking sector's default risk improved, and the risk-premium came down. As a result, the effective yield is likely to be much lower at the time of repayment compared to the time of investment.

[22]The original terms in the EESA (Emergency Economic Stabilization Act of 2008) required the Treasury to dispose of warrants when 'the market [was] optimal for such assets, in order to maximize the value for taxpayers'. The ARRA passed in February 2009 amended the EESA to require the Treasury to 'liquidate' warrants after repayment. Although the contract stipulates that warrants must be repurchased at fair market value, market benchmarks for such instruments (call options with 10 year maturities) are scarcely available.

To estimate the repayment subsidy given to banks, we first compute the prevailing market yield on preferred equity at the time of repayment. We compute the average preferred equity yield based on the sample of banks for which we have the individual preferred equity data. Since the average duration for preferred equity is over 40 years while the TARP investment had a duration of only 1-2 years based on realized cash flows, we need to make some adjustments to account for the maturity difference. We do so in two steps. We first compute the spread on preferred equity as the difference between preferred equity yield and 30-year treasury yield at the time of repayment.[23] In the second step, we add the spread to 2-year treasury yield to estimate the preferred equity yield in the market at the time.

We compute the repayment subsidy as the NPV of the originally promised cashflows until three years from the investment date discounted at the prevailing preferred equity yield. We divide the estimate by the par value of the TARP amount to obtain a percentage measure of subsidy for each recipient.[24] Table 2.5 contains the results of this exercise. We find that the average preferred equity yield in the market is 4.05% at the time of TARP repayment, compared to 5% coupon on TARP. On an equal weighted basis we find that the repayment subsidy is 0.7%. On a value-weighted basis, the subsidy is 1.1%. In other words, allowing banks to repay TARP early at par value had an opportunity cost of approximately $2 billion based on the yield of comparable market securities at the time of repayment.

[See Table 2.5]

The subsidy that came from relatively attractive terms at the time of the bailout was provided to banks in a distressed state of the world. In contrast, the prepayment subsidy was provided after markets had recovered. While providing a subsidy to avoid negative externalities in a crisis state is warranted, there is no clear economic justification for providing

[23]Although our preferred equity index has an average duration of 40 years, the closest publicly traded treasury benchmark is a 30 year treasury bond. We compute the average preferred equity yield on a daily basis using the sample of banks with fixed rate coupons with fixed maturities. Our results remain similar if we consider preferred equity with a floating rate coupon without subtracting the 30-year treasury yield.

[24]A small fraction of banks (less than 2% on a value-weighted basis) repaid TARP in multiple installments. For these banks, we only compute the repayment subsidy using the final payment installment. This does not qualitatively or quantitatively alter the results.

banks a subsidy after financial markets recover. These results provide an immediate policy recommendation for future bailout designs: the prepayment must accompany a penalty if done in a good state of the world. Alternatively, these securities can be sold in an auction to better capture the present value of their expected future cash flows.

2.5 Warrant Disposition Renegotiation

We conduct an event study centered around the June 26, 2009 announcement of the Treasury's framework to repurchase warrants.[25] Under this framework, a bank can repurchase its warrant if the Treasury accepts its bid, otherwise warrants are auctioned in the open market. If markets anticipate that the Treasury's repurchases of TARP warrants are fairly priced, the announcement of this framework should have no effect on a bank's stock return. Alternatively, if common equity holders anticipate the terms of the warrant repurchases to be favorable, then there is likely to be a positive effect on stock returns. We test this hypothesis by measuring the bank's cumulative abnormal returns using a (-1,+1) three-day window centered around June 26, 2009. In order to measure the economic value received by the shareholders due to the warrant disposal, we value weight the event window stock returns using the market equity value, measured just before the event window, as the weight. We pool all banks with outstanding warrants together in this test because it was not clear at the time which banks' warrants would be repurchased or sold. Next, we conduct a staggered event study around the date that a bank announced its warrant transaction price to the public and whether its warrant was repurchased or sold in an auction.

Table 2.6 contains the results.[26] Panel A documents a positive and highly significant stock return of 4.4% around the June 26, 2009 event window. After adjusting for the CAPM model returns, the cumulative abnormal return remains a highly significant 1.7% during this window. Therefore, shareholders gained from the initial announcement of early warrant

[25] See www.treasury.gov/press-center/press-releases/Pages/200962612255225533.aspx

[26] In this analysis, the sample size for banks with warrant disposition information decreases from 160 to 135 because some banks do not have CRSP data coverage to compute abnormal returns. The betas used to compute abnormal returns are estimated from a monthly CAPM, and following Bayazitova and Shivdasani (2012), we estimate these parameters over Jan 2007 to Sept 2008 before any policy intervention.

disposition.

[See Table 2.6]

Panel B contains the results of the staggered event study in which details of the warrant price and method of disposition were announced. Consistent with markets anticipating a repurchase subsidy from the June 26 announcement, we find no statistically significant abnormal return for banks whose warrants were repurchased. We do find, however, a statistically significant negative abnormal return of -1.7% for the subsample of banks whose warrants were sold at auction. Said differently, positive returns that banks earned on the initial announcement date did not disappear when they were successful in buying their warrants back from the Treasury. On the other hand, if they were unable to do so, the entire positive return was lost. This analysis reveals that bank shareholders captured some of the taxpayer gains of TARP investments via warrant repurchase at favorable terms.

To better understand the source of the warrant repurchase subsidy, we analyze the Treasury's methodology in determining 'fair' repurchase prices.[27] The Treasury uses a binomial approximation to the Black-Scholes model. The key input to this valuation is the 10-year forward volatility, for which few, if any, market benchmarks exist. In practice, the Treasury took a linear interpolation between the implied volatility of a shorter maturity option and the bank's 10-year historical volatility to arrive at its volatility estimate for estimating the warrant's fair value. The Treasury, however, used a winsorized version of the 10-year historical volatility. By cutting out tail observations, which might especially matter over a 10-year business cycle, the model could be significantly underestimating the true 10-year forward volatility.

In the next set of analyses, we compare the non-winsorized 10-year historical volatility from CRSP to the implied volatility from the Treasury's warrant repurchase price.[28] We

[27] The full report on the Treasury's warrant valuation methodology is available at `https://www.treasury.gov/initiatives/financial-stability/TARP-Programs/bank-investment-programs/cap/Documents/Jarrow%20TARP%20Warrants%20Valuation%20Method.pdf`

[28] To match the Treasury's methodology, we compute the 10-year historical volatility using daily returns. We have 57 banks for which we are able to compute the 10-year historical volatility.

define 'Volatility Subsidy' as the difference between the two volatility estimates. We also compute an alternate measure of 'Volatility Subsidy' using the implied volatility from the longest dated traded call-option from OptionMetric. If the term structure of volatility is upward sloping, this should provide a market-based lower bound on the subsidy. Table 2.7 presents the results. Panel A finds that the 10-year historical volatilities from CRSP is 18.5% higher than the implied volatilities used by the Treasury. The difference is highly statistically significant. Column (2) shows that the option implied volatility is 10.4% higher than the Treasury's implied volatility.

[See Table 2.7]

In other words, banks likely repurchased these warrants at a favorable price from the Treasury since the volatility estimate is the key driver of warrant valuation. Since we do not observe the forward volatility, the 'true' estimate of volatility is always model dependent and subject to debate. Therefore, we relate the volatility subsidy to the banks' stock market reactions to assess whether markets considered these repurchase prices as favorable or not. We regress a measure of volatility subsidy on the cumulative announcement day return in (-1,+1) window around the warrant disposal day. Specifically, for each bank we first compute the difference between warrant value using historical volatility and the Treasury's volatility estimate. We scale the valuation difference by the asset value of the bank and create a variable 'High Volatility Subsidy' that equals one if the scaled subsidy is above the sample median, zero otherwise. Panel B presents the results. We find that banks with higher estimated volatility subsidies from the Treasury experience larger abnormal returns around their warrant repurchase dates. This substantiates the claim that the banks were able to repurchase their warrants at a favorable estimate of volatility, which in turn limited the upside gains of the taxpayers.

Overall, our results document three key findings: (a) banks received significant subsidy compared to private benchmarks, (b) prepayment of preferred equity without any penalty contributed to the subsidy, and (c) warrant repurchases favored the financial institutions. We provide a bank-by-bank summary of these estimates in Table 2.8 for the sample of 20 banks for which we have data on traded preferred equity in private markets.

[See Table 2.8]

2.5 Payout Decisions

We now examine which financial stakeholders benefited from TARP subsidies. In particular, we consider how banks receiving larger subsidies distributed these gains through dividend payments to common equity holders and compensation to the CEOs following the repayment of TARP. Investigating changes in these payouts is particularly apt since TARP prohibited any increase in dividends per share and CEO compensation until the principal was repaid. This gave banks an incentive to renegotiate and quickly repay TARP investments. Understanding the relationship between payouts and TARP renegotiation is also important from the perspective of financial stability and risk-taking in banks. For example, Meiselman et al. (2018) document that banks with high payout in good times perform worse during a crisis. Since post-renegotiation payouts occurred in relatively good states of the world, increased payout during this period has important implications for the banking sector's performance in bad times in the future.

To test how banks change their payouts around repayments, we construct a bank-year panel of CEO compensation and dividend payouts from 2005 to 2015. We measure the outcome variables, 'CEO Payout' and 'Dividend Payout' using a bank's total CEO compensation and dollar amount of dividend payments scaled by the levels of these variables in the pre-crisis years of 2002-2007. Therefore, the dependent variables measure the level of payout in a year relative to their average values in the pre-crisis period.

Banks repaid TARP in different years. We therefore use a dynamic event study specification since using a static difference-in-differences specification when units have different treatment timing may result in severe bias (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2020).[29] In the dynamic specification, we create indicator

[29]We estimate the dynamic model using OLS in the paper but also find the results are robust to using the Sun and Abraham (2020) estimator which accounts for the presence of heterogeneous treatment effects.

variables for every year relative to the year of repayment of TARP by the bank. For instance, 'Repayment Year = + 1' equals one in the year after TARP repayment, zero otherwise. We then split the sample into banks with above and below median 'Investment NPV' (i.e., TARP NPV on a per dollar basis) to test how banks with larger subsidies distributed higher payouts to their stakeholders.

Table 2.9 presents the results. Columns (1) & (2) contain the results for CEO compensation. CEO payout increased considerably for the high subsidy group for a period of three years after the repayment. In contrast, banks receiving low subsidies experience no increase in CEO compensation. Columns (5) & (6) show that the high subsidy banks significantly increased their dividend payouts to shareholders in the years following the TARP repayment.

[See Table 2.9]

Our earlier results document that banks that were successful in repurchasing their warrants from the Treasury received significant subsidies. We next test whether CEOs were able to capture some rents from these renegotiations. Columns (3) & (4) of Table 2.9 present the results of CEO payout across banks there were able to repurchase their shares versus banks whose warrants were sold in the market. CEO compensation for banks that repurchased their warrants from the Treasury increased consistently by a significant amount, ranging from 51% to 93% of pre-crisis levels, in the years following the repayment. On the other hand, for banks whose warrants were sold in the market, CEO's compensation did not increase. The evidence supports the view that bank managers captured some of the rents provided by warrant repurchase subsidies.

2.5 Additional Analyses & Robustness Tests

We conduct a series of robustness tests and additional analyses in this section of the paper to rule out some alternative explanations and to provide additional economic insights into our results.

2.5 Benchmark Returns and Policy Uncertainty:

As discussed in Section 2.3, market participants faced two types of risk during the early days of the crisis: the uncertainty about the policy intervention itself and conditional on the resolution of this uncertainty the risk of investing in financial institutions with high default risk. Therefore, our subsidy measure can potentially capture both of these effects. While we cannot directly decompose the subsidy into these two parts, we devise a test that measures the private market return after uncertainty over the policy actions, and therefore aggregate stability of the financial sector, diminished. In this test we compare TARP's return with the return earned by a market investor in the preferred equity of the banks six, nine, or one-year after the TARP investment date.

Figure 2.5 plots the distribution of subsidy using the 9-month shifted version of the benchmark return. On average, taxpayers earned 10.8% lower return compared to benchmark return shifted by a period of nine months. Table A.16 of the Online Appendix presents the results of this analysis for all three versions of shifted return, i.e., benchmark returns shifted by six, nine, and twelve months. Even with the most conservative 1-year benchmark, banks received a 6% subsidy relative to the private market. This analysis indicates TARP investments earned a lower return than a private market investor who invested in these banks at a time when concerns about the uncertainty surrounding the policy interventions and aggregate stability of the banking sector were resolved for all practical purposes.

[See Figure 2.5]

2.5 Liquidity of Benchmark Returns:

Financial markets did not function smoothly soon after the failure of Lehman Brothers. Therefore, one may be concerned that our benchmark return does not represent an investible strategy for private market investors. To address this issue more directly, we compute the average bid-ask spread of preferred equity prices during the crisis period. We plot the evolution of half of the bid-ask spread on these securities in Figure A.13 of the Online Appendix, as they represent the trading costs an investor would incur in purchasing the security (Stoll, 2000; Bao et al., 2018). As expected, the half spread widened from a level of 25 basis points during the pre-crisis period to a peak of 170 basis points at the time of Lehman's failure. At the time of CPP investments, however, the spread came down to a level of 40 basis points. Even if we take the peak full spread of 3.4% as the representative cost of transactions for the benchmark securities, it is significantly lower than our subsidy estimate of 30%. Second, our benchmarking exercise based on the Warren Buffett deal in Goldman Sachs does not suffer from this critique since the benchmark returns were also from a privately placed investment. Finally, our benchmarks based on shifted returns, i.e. benchmark returns shifted by 6-12 months, further ameliorates concerns about lack of liquidity affecting our results because by that time the markets were functioning reasonably smoothly.

Further, we collect evidence from the existing literature on the economic magnitude of returns that investors earn due to such market breakdown. Pasquariello (2014) constructs a measure of market dislocation based on the violation of some standard arbitrage conditions in equity, foreign currency and money markets during the 2008 crisis. He shows that stocks more sensitive to the dislocation, i.e., stocks that are more likely to be affected by the market breakdown, earn a higher expected return. In terms of economic magnitude, the difference in annualized abnormal return is about 5.3% per annum between stocks that fall in the bottom versus the top decline of this beta. Our estimated subsidy of 30% per annum is too large to be explained by even the differences in expected return across extreme portfolios documented by these studies.

2.5 Realized versus Expected Returns:

Another potential concern with our empirical analysis can come from the difference in realized and expected returns on our benchmark securities. Specifically, our returns are based on one possible realization of the states of the world. If our replication exercise is perfect, then there is no concern about the subsidy calculation. However, the presence of warrants makes the replication exercise imperfect and hence raises a concern. Could the TARP's realized return on warrants be much higher under a different realization, making our subsidy calculation biased upward? There are three key features of our analysis that make this concern a relatively minor one. First, our realized returns come from a relatively good state of the world; hence the warrant payoffs are already large. Second, the fact that warrant terms were renegotiated ex post suggests that their payoff is capped even in more attractive states of the world. Finally, as shown by Veronesi and Zingales (2010), warrant comprised a relatively modest part of the investment based on ex ante valuation.

2.5 Sensitivity Analysis

We perform a sensitivity analysis to see how TARP subsidies change if upfront contract terms were set differently. We generate a series of counterfactual cashflows assuming either the preferred equity coupon was larger or the Treasury received additional warrant shares. We then recompute NPV by discounting these cashflows holding constant the capital market benchmarks. Online Table A.17 contains the results. For the NPV to become zero, i.e. for the Treasury to break even on TARP, we find that the warrant shares must be 80-100% of the principal amount holding all other terms of the contract fixed. Alternatively, the coupon rate on preferred equity must be as high as 40% holding all other terms fixed. As shown earlier, Warren Buffett's deal had a much higher coupon rate and warrant amounts attached to the investment, similar to the results of our sensitivity analysis.

2.6 Conclusions

Government bailouts happen in bad times, but the repayments are received in good times. At the time of investments, recipients have higher risk and the risk aversion in the economy is high as well. Therefore, from a purely financial perspective, firms raising capital at a time like this should pay sufficiently high returns to compensate their investors for bearing this risk. Using returns on several benchmarks of comparable or lower risk than the preferred equity investments made under TARP, we show that the recipients paid a much lower rate of return to the U.S. Treasury compared to the benchmarks. Contrary to the popular claims that TARP investments were "profitable" for the taxpayers on a purely financial basis, our analysis shows that they were heavily subsidized on a risk-adjusted basis. In addition, ex post renegotiation of TARP terms further contributed to the subsidy enjoyed by the banks.

Our analysis does not speak to the issue of social costs and benefits. Indeed, an objective of the program was to stabilize the economy and bring financial stability to the system. We do not comment on that objective of the program, and therefore our analysis makes no welfare claim. However, our analysis provides an important input to any welfare analysis for TARP.

Our findings have important implications for the design of future bailouts, both in terms of ex ante terms of the contract and ex post renegotiation. In TARP's case, the renegotiation of the contract benefited shareholders at the expense of the taxpayers. Since these renegotiations happened in relatively better states of the world, it is not clear that relaxing the contract terms in favor of the recipients has any value for financial stability. Instead, our findings suggest that the relaxation of contract terms helped banks pay high dividends, which in turn weakens their capital position. These inputs should be helpful for the design and implementation of future bailouts.

2.7 Tables and Figures

Figure 2.1. Bank CDS Spread

Figure 2.1 plots the Banks' CDS Spreads over the TARP CPP investment horizon. Bank Index CDS Spread is measured by the DS North America Banks 5 Year Credit Default Swap Index. The dotted line labeled 'TARP Announcement' corresponds to the TARP announcement on October 13th 2008. 'Initial TARP Investment' is the date of the first TARP investment date on October 28th 2008. The dotted line labeled 'Original Maturity' is the average earliest repayment date stipulated in the original TARP CPP Term Sheet. The dotted line labeled 'Early Repayment' is the average TARP CPP repayment date conditional on repaying before the original maturity.

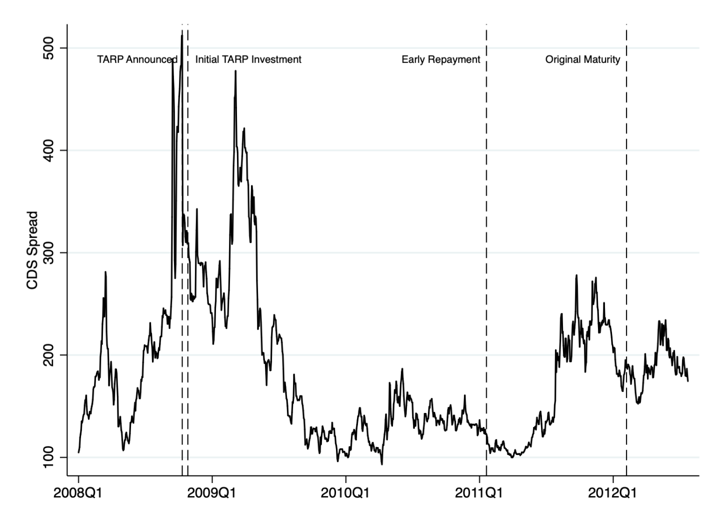

Figure 2.2. Benchmark Preferred Equity Index

Figure 2.2 plots the daily cumulative returns realized by S&P US Preferred Stock Index over the TARP CPP investment horizon. The cumulative return is normalized to zero on January 1st 2008.

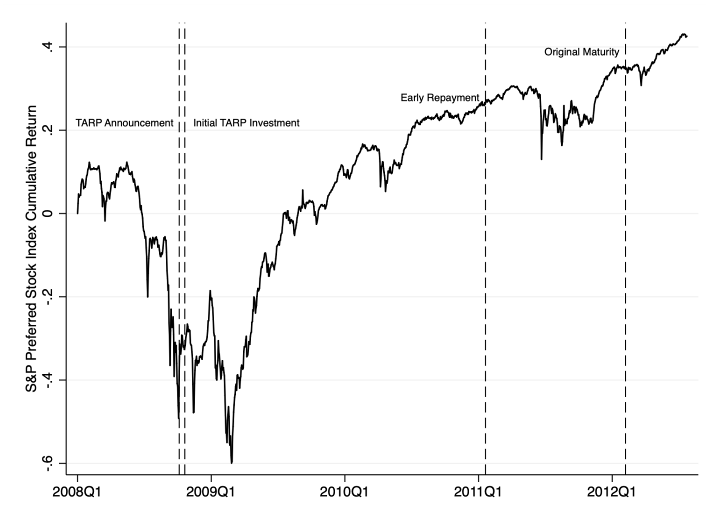

Figure 2.3. TARP Investment Timeline

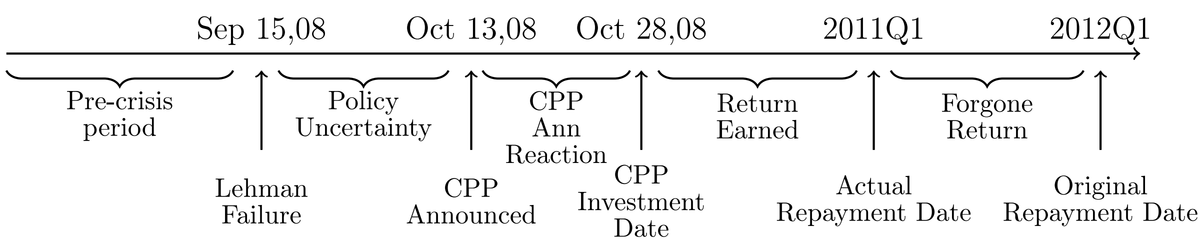

Figure 2.4. TARP Investment v. Same Bank Preferred Equity

Figure 2.4 compares a bank's TARP CPP Return to the same bank's preferred equity return using the same buy and sell horizon as the TARP investment. Both returns are annualized.

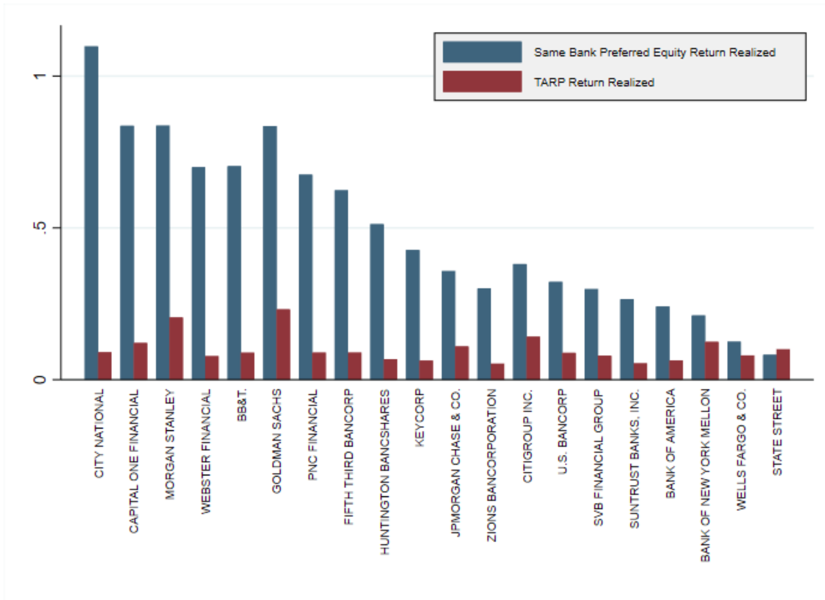

Figure 2.5. TARP Benchmark Adjusted For Policy Uncertainty

Figure 2.5 plots a histogram distribution of TARP subsidy (i.e., the difference between the annualized rate of return from investing in a bank's preferred equity and the TARP return) using an alternative benchmark that shifts the investment horizon of the benchmark by 9 months from the date of the original investment.

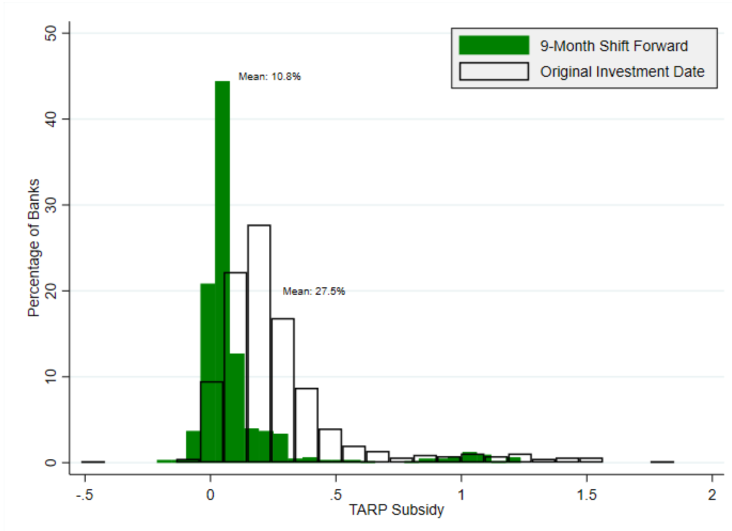

TABLE 2.1. Summary Statistics

Table 2.1 presents summary statistics for banks receiving TARP CPP investments. TARP Investment Amt. is the total investment a bank received through the TARP CPP program. Investment Date is the year-month in which a bank's first TARP investment was made. Investment Maturity is the number of years from the initial investment until the bank both repaid the TARP investment principal and repurchased/sold its warrant. EW Investment Maturity is the equal weighted maturity across all banks. VW Investment Maturity is value weighted maturity using the CPP investment amount as the weight. TARP Cash Back is the total cash received by the Treasury under the program.

	Mean	SD	Min	P25	P50	P75	Max	N
TARP Investment Amt. ($ Millions)	312.90	2100.90	0.30	5.00	11.73	35.00	25000.00	653
Investment Date	2009m1	2.64	2008m10	2008m12	2009m1	2009m3	2009m12	653
Investment Maturity (Years)	3.15	1.54	0.20	2.24	2.98	4.03	9.26	653
EW Investment Maturity (Years Until Warrant Disposal)	3.39	1.64	0.24	2.37	3.29	4.34	9.49	653
VW Investment Maturity (Years Until Warrant Disposal)	1.71	1.17	0.24	1.13	1.35	2.24	9.49	653
TARP Cash Back ($ Millions)	346.24	2387.24	0.00	4.68	11.94	33.82	32839.27	653

TABLE 2.2. Benchmark Returns

Table 2.2 compares TARP returns to various public market benchmarks. TARP Return Realized is calculated as the annualized internal rate of return of TARP cash flows. TARP Subsidy is the difference between a benchmark index return and TARP's return. EW Return is the equal-weighted return across banks. VW Return is the value-weighted return using the original TARP investment amount as the weight. S&P US Preferred Stock Index Return Realized is the annualized rate of return from investing in the S&P US Preferred Stock Index for the same investment horizon as that of bank's TARP investment. Same Bank Preferred Equity Return Realized is computed using the same bank's preferred equity returns and the same investment horizon as that bank's TARP investment. Preferred Equity With Warrant Return Realized is computed using the returns to a replicating portfolio with a 90% weight to preferred equity claims and 10% in warrants. The warrant returns are calculated following the Treasury's methodology of valuing the claims as an American Call Option on a dividend paying stock using a binomial approximation of Black-Scholes model. The TARP with Buffett Terms benchmark is computed by taking the IRR of a bank's cash-flows if the TARP investment had the same terms as Buffett's investment in Goldman Sachs. Same Bank Senior Bond Return Realized is computed using the same bank's senior bond returns. Individual bank preferred equity returns are taken from Refinitiv Datastream using the most recent preferred equity issue prior to 2008 with trading data available until the end of the original TARP maturity.

	EW Return		VW Return		Obs.
Panel A: Same Bank Preferred Equity					
TARP Return Realized (Same Bank Sample)	0.10***	(9.66)	0.11***	(9.90)	20
Individual Bank Prefered Equity Return Realized	0.49***	(7.84)	0.40***	(7.42)	20
TARP Subsidy (Difference)	0.39***	(6.61)	0.29***	(6.20)	20
Panel B: Preferred Equity Index					
TARP Return Realized	-0.01	(-0.82)	0.09***	(15.21)	653
S&P Preferred Stock Index Return Realized	0.27***	(37.80)	0.39***	(70.85)	653
TARP Subsidy (Difference)	0.28***	(25.16)	0.30***	(39.68)	653
Panel C: Pref. Equity with Warrant					
TARP Return Realized (Same Bank Replicating)	0.10***	(9.33)	0.11***	(9.63)	19
Preferred Equity With Warrant Return Realized	0.50***	(7.34)	0.40***	(6.26)	19
TARP Subsidy (Difference)	0.39***	(6.33)	0.29***	(5.19)	19
Panel D: TARP with Buffett Terms					
TARP Return Realized	-0.01	(-0.82)	0.09***	(15.21)	653
Buffett IRR	0.23***	(13.25)	0.59***	(27.30)	653
TARP Subsidy (Difference)	0.24***	(18.54)	0.50***	(27.47)	653
Panel E: Same Bank Bond					
TARP Return Realized (Same Bank Bond Sample)	0.12***	(8.50)	0.12***	(9.34)	21
Individual Bank Senior Bond Return Realized	0.19***	(6.78)	0.20***	(6.61)	21
TARP Subsidy (Difference)	0.07***	(2.90)	0.08***	(3.29)	21

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.3. NPV of TARP Investments

Table 2.3 presents statistics on the NPV of TARP investments. Panel A presents the NPV for the full bank sample. For the full bank sample, NPV is calculated by discounting back the net cash flows from TARP investments using the cumulative returns on the S&P US Preferred Stock Index. 'NPV / Investment' and 'NPV / Assets' normalizes 'Dollar NPV of TARP' using the TARP investment amount and total bank assets, respectively. Panel B calculates NPV for individual banks with traded preferred equity. For the preferred equity bank sample, NPV is calculated by discounting back the cash flows from TARP investments using the cumulative returns on the same bank's preferred equity. Note that a negative NPV corresponds to a positive TARP subsidy.

Panel A: Full Sample

	Mean	SD	Min	P25	P50	P75	Max	N
NPV of TARP ($ Billions)	-0.083	0.531	-7.707	-0.014	-0.005	-0.002	0.093	653
NPV / Investment	-0.435	0.228	-1.030	-0.535	-0.400	-0.320	0.297	653
NPV / Assets	-0.009	0.009	-0.107	-0.011	-0.008	-0.005	0.005	197

Panel B: Same Bank Preferred Equity Sample

NPV of TARP ($ Billions)	-1.701	2.007	-8.860	-2.395	-1.184	-0.293	-0.003	20
NPV / Investment	-0.306	0.194	-0.596	-0.495	-0.309	-0.117	-0.001	20
NPV / Assets	-0.007	0.005	-0.016	-0.013	-0.005	-0.002	-0.000	20

TABLE 2.4. Renegotiation of TARP Contracts

Table 2.4 presents descriptive statistics on the renegotiation of TARP contracts. 'Repaid Early' is an indicator equal to 1 if a bank repaid the preferred equity principal before the minimum contractual maturity of three years. 'Investment Maturity' is the number of years that a bank took to repay the principal of TARP conditional on early repayment. 'Includes Common Stock Warrants' is an indicator equal to one if the TARP investment included warrants on publicly traded common stock. 'Warrant Disposition Data Available' is an indicator variable equal to one if the banks' warrant disposition information is included in the Treasury's 2012 warrant disposition report. 'Warrant Repurchased by Bank' indicates that the Treasury repurchased the warrant from the bank at a negotiated price. 'Warrant Sold at Auction' indicates that the Treasury sold the warrant at auction to market participants. The Value-Weighted column computes averages using the original TARP investment amount as the weight.

	Equal-Weighted		Value-Weighted	
	Mean	N	Mean	N
Early Repayment				
Repaid Early	0.466	653	0.904	653
Investment Maturity (Years Condo. on Early Repayment)	1.939	304	1.190	304
Warrant Disposition				
Includes Common Stock Warrants	0.452	653	0.980	653
Warrant Disposition Data Available	0.245	653	0.953	653
Warrant Repurchased by Bank	0.756	160	0.493	160
Warrant Sold at Auction	0.244	160	0.507	160

TABLE 2.5. Early Repayment Subsidy

Table 2.5 reports the early repayment subsidy banks received. 'Repayment Subsidy' is the NPV of the remaining scheduled preferred equity cashflows (5% coupon + principal repayment at three years maturity) scaled by the investment amount of those cash-flows. The discount rate, labeled as the (Adjusted) Perf. Equity Yield at Repayment', is taken as the market based average preferred equity yield at the time of repayment, adjusted for differences in maturity with respect to the remaining TARP cash-flows. 'Remaining Maturity at Repayment' is the number of years at the time of repayment until the original three-year minimum maturity. The value-weighted column computes averages using the original TARP investment amount as the weight.

	Equal-Weighted		Value-Weighted	
Repayment Subsidy	0.677***	(6.175)	1.051***	(16.417)
(Adjusted) Pref. Equity Yield at Repayment	4.050***	(70.733)	4.247***	(107.807)
Remaining Maturity at Repayment	1.061***	(23.457)	1.810***	(49.597)

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.6. Warrant Disposition Event Study

Table 2.6 reports the bank stock price reactions to the announcement of bank repurchases of TARP warrants. In Panel A, the event study window is centered around a single day, June 26 2009, when the Treasury announced its framework for repurchasing TARP warrants "quickly". In Panel B, the event window is centered on the date when a bank announced its warrant transaction price and whether the warrant was repurchased by the bank or auctioned to market participants. Panel B reports CARs separately for banks with repurchased and auctioned (sold) warrants and tests the difference between them. Returns and cumulative abnormal returns are calculated using a (-1,1) three day window using the CRSP VW index in a CAPM model. The mean returns are value weighted by banks' market equity and standard errors are clustered at the bank level.

Panel A: Warrant Repurchase Process Announced

	(-1,1) Event Return	
Raw Bank Return	0.044***	(9.24)
CAR	0.017**	(2.23)
Observations	135	

Panel B: (Staggered) Warrant Transaction Price Disclosed

	(-1,1) Event Return	
Warrant Repurchased		
Raw Bank Return	0.016**	(2.51)
CAR	0.002	(0.31)
Observations	101	
Warrant Sold at Auction		
Raw Bank Return	-0.013***	(-4.43)
CAR	-0.017***	(-3.51)
Observations	34	
Difference		
Raw Bank Return	0.029***	(4.09)
CAR	0.019**	(2.39)
Observations	135	

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.7. TARP Warrant Subsidy

Table 2.7 estimates the warrant volatility subsidy provided by the Treasury to banks and relates it to the warrant event study returns. Panel A presents the mean 'Volatility Subsidy', which is defined as the difference between a bank's 10-year historical volatility and the implied volatility of the Treasury's repurchase price for that bank. In the second column of Panel A, we estimate the 'Volatility Subsidy' using the implied volatility on the longest dated call option covered on OptionMetric. Panel B regresses the (-1,1) CAR from Panel B of Table 2.6 on whether a bank received a large warrant subsidy. 'High Volatility Subsidy' is equal to one if (Historical Vol. Warrant Price - Treasury Warrant Price)$\times$ Warrant Shares divided by Assets is above the sample median. Standard errors are clustered at the bank level.

Panel A: Warrant Volatility Subsidy

	Historical 10-yr	Implied Longest-Mat
Mean Volatility Subsidy	0.185***	0.104***
	(12.84)	(6.59)
N	57	33

Panel B: Event Study Heterogeneity

	(-1,1) CAR	
	(1)	(2)
High Volatility Subsidy	0.019**	0.021**
	(2.46)	(2.44)
Cash/Assets		-0.010
		(-0.25)
Log(Assets)		0.004
		(1.49)
Constant	-0.014***	-0.073*
	(-2.88)	(-1.82)
N	57	57
R^2	0.10	0.15

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 2.8. Bank-by-Bank Subsidy Estimates

Table 2.8 provides a bank-by-bank summary of the subsidy estimates for the sample of 20 banks with traded preferred equity in private markets. Investment Amt. is the dollar amount of the CPP investment in ($) billions. IRR Preferred is the annualized return on the same banks' preferred equity over the same investment horizon as the Treasury's TARP investment. IRR Treasury is the annualized internal rate of return of the cash flows that banks pay the Treasury. Subsidy (% Difference) is the difference between the two IRRs. Subsidy ($Billions) is the NPV of the banks' cash flows paid to the Treasury discounted by the cumulative return on the same bank's preferred equity. Repayment Subsidy is the NPV of the remaining TARP cash flows at the time a bank repaid TARP divided by the outstanding principal amount. The repayment subsidy NPV is computed using the prevailing preferred equity yield as the discount rate. Warrant Subsidy is the difference between TARP repurchase price of a banks' warrants and the estimated dollar value from an American Call Option using a binomial approximation and a bank's unwinsorized 10-yr historical volatility. We scale dollar difference by the total TARP investment amount. 'Sold at Auction' indicates that bank's warrant was sold to market participants rather than repurchased by the bank.

Bank Name	Investment Amt. ($Billions)	IRR Preferred	IRR Treasury	Subsidy (% Difference)	Subsidy ($Billions)	Repayment Subsidy	Warrant Subsidy
CITIGROUP INC.	25.0	38.08%	14.16%	23.92%	8.86	Converted	Sold at Auction
JPMORGAN CHASE	25.0	35.77%	10.95%	24.82%	3.52	0.02%	Sold at Auction
BANK OF AMERICA	25.0	24.10%	6.31%	17.79%	2.35	1.38%	Sold at Auction
WELLS FARGO	25.0	12.51%	7.99%	4.52%	1.65	1.65%	Sold at Auction
MORGAN STANLEY	10.0	83.68%	20.50%	63.18%	2.89	0.02%	3.71%
GOLDMAN SACHS	10.0	83.53%	23.16%	60.37%	2.44	0.02%	0.20%
PNC FINANCIAL	7.6	67.54%	8.91%	58.62%	3.14	2.81%	Sold at Auction
U.S. BANCORP	6.6	32.23%	8.84%	23.39%	0.35	0.94%	0.14%
SUNTRUST BANKS	4.9	26.52%	5.38%	21.15%	1.72	1.72%	Sold at Auction
CAPITAL ONE	3.6	83.63%	12.10%	71.54%	1.17	0.94%	Sold at Auction
FIFTH THIRD BANCORP	3.4	62.38%	8.92%	53.46%	1.85	2.27%	5.04%
BB&T CORP.	3.1	70.34%	8.89%	61.45%	0.79	0.94%	0.92%
BANK OF NEW YORK MELLON	3.0	21.15%	12.46%	8.69%	0.10	0.02%	1.25%
KEYCORP	2.5	42.71%	6.27%	36.44%	1.20	1.72%	3.26%
STATE STREET	2.0	8.20%	10.00%	-1.80%	0.00	0.02%	0.86%
ZIONS BANCORPORATION	1.4	30.08%	5.27%	24.81%	0.76	No Early Repayment	Sold at Auction
HUNTINGTON BANCSHARES	1.4	51.23%	6.76%	44.47%	0.71	2.02%	3.98%
WEBSTER FINANCIAL	0.4	70.00%	7.75%	62.25%	0.22	2.03%	Sold at Auction
CITY NATIONAL	0.4	109.78%	9.02%	100.76%	0.24	2.38%	1.77%
SVB FINANCIAL GROUP	0.2	29.83%	7.91%	21.92%	0.06	2.39%	0.03%

TABLE 2.9. Financial Stakeholder Payouts

Table 2.9 examines changes in financial stakeholder payouts around TARP repayments sorted by the TARP subsidy a bank received. The panel consists of bank-year observations from 2005 - 2015 for all banks covered by Bank CRSP-Compustat. Samples are split into 'Low Subsidy' and 'High Subsidy' based on whether a bank's NPV/Investment is above or below sample median. In columns (1)-(4), the outcome variable is 'CEO Payout' which is defined as annual CEO compensation scaled by the average level of CEO compensation in the pre-crisis years of 2002-2007. In columns (5) & (6), the outcome variable is 'Dividend Payout' which is defined as annual dividends scaled by the average level of dividends payments in the pre-crisis years 2002-2007. Outcome variables are winsorized at the 2% level. 'Repayment Year =0' is an indicator variable equal to one in the year that a bank repaid the TARP principal in full. 'Repayment Year = +1' equals one in the year after a bank repaid TARP, and so on. Standard errors are clustered at the bank level.

	CEO Payout				Dividend Payout	
	(1) Low Subs.	(2) High Subs.	(3) Sold	(4) Repurchased	(5) Low Subs.	(6) High Subs.
Repayment Year = -3	0.109	-0.047	0.300*	-0.223*	-0.094	0.014
	(0.56)	(-0.66)	(1.82)	(-2.01)	(-0.81)	(0.15)
Repayment Year = -2	-0.020	-0.044	0.135	-0.076	-0.168*	0.236*
	(-0.17)	(-0.56)	(1.10)	(-0.80)	(-1.83)	(1.75)
Repayment Year = 0	0.023	0.595***	-0.002	0.515***	-0.268	0.264**
	(0.11)	(3.30)	(-0.01)	(2.78)	(-1.08)	(2.04)
Repayment Year = +1	-0.129	0.672***	-0.188	0.604***	-0.386	0.633***
	(-0.48)	(3.13)	(-0.76)	(3.11)	(-1.14)	(3.00)
Repayment Year = +2	-0.179	0.956**	-0.528	0.774**	-0.197	1.039***
	(-0.51)	(2.59)	(-1.53)	(2.69)	(-0.47)	(3.48)
Repayment Year = +3	-0.379	0.947*	-0.736	0.756**	-0.433	1.194***
	(-0.83)	(1.98)	(-1.48)	(2.03)	(-0.82)	(3.00)
Repayment Year ≥ 4	-0.251	1.335*	-0.624	0.936*	-0.538	2.193***
	(-0.39)	(1.89)	(-0.79)	(1.79)	(-0.79)	(3.00)
Observations	421	341	220	397	1062	1027
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.585	0.599	0.606	0.617	0.508	0.480
Within R^2	0.007	0.060	0.033	0.046	0.006	0.035

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Chapter 3: Why Do Banks Hide Losses?

This chapter coauthored with Amiyatosh Purnanandam of the Ross School of Business, University of Michigan,

3.1 Introduction

Intermediation comes with opacity. Banks specialize in making loans to opaque borrowers, and consequently, their activities become nontransparent to outsiders. Therefore, truthful reporting of banks' profitability and riskiness is vital for almost all banking regulations such as capital requirements, deposit insurance premiums, and bailout assistance, to name a few. Market discipline too becomes ineffective if banks' reported profits and risks deviate from their actual values.[1] Hence a careful examination of the economic drivers of truthful reporting is of utmost importance to the banking literature. Unfortunately, there is very limited empirical evidence on this important issue: we simply do not get to observe what banks are hiding.[2]

While we do get to see sporadic episodes of misreporting of profits and bad loans when banks are caught by the regulators, it is rare to find systematic data on underreporting of losses by the entire banking sector of an economy.[3] Our paper exploits an unexpected

[1]Pillar 3 of the Basel Committee on Banking Supervision is exclusively focused on this issue: "Pillar 3 of the Basel Framework lays out a comprehensive set of public disclosure requirements that seek to provide market participants with sufficient information to assess an internationally active bank's material risks and capital adequacy."

[2]There is a growing literature on the importance of loan loss provisioning for bank stability (e.g., see Bischof et al. (2020)). We contribute to this literature by exploiting an empirical setting where we are able to verify ex-post the accuracy of reporting based on a regulatory audit.

[3]For example, Wells Fargo hid $1.2 billion of bad loans before the housing crash of 2008-09 to qualify for the FHA insurance. Regions Bank misclassified $164 millions of losses in 2009, which was uncovered by the SEC in 2014.

event in the Indian banking sector, where a policy change by the central bank of India (the Reserve Bank of India, or RBI in the rest of the paper) in 2015 mandated all banks to come clean on the extent of bad loans they had been hiding in their financial reports. After a sector-wide supervisory audit, banks were now required to report both the extent of underreporting of non-performing loans (NPLs), and consequently the overreporting of profits due to inadequate provisioning against the hidden losses.[4] The economic magnitude of this shock was large: collectively banks had reported profits of over $9 billion during 2016 and 2017 before accounting for the hidden losses. Once these losses were accounted for, as per the RBI's new disclosure policy, profits dropped to less than half at about $4 billion.

The unexpected revelation of these losses that have been building up due to decisions taken in the past by the bankers provides us with an unparalleled opportunity to study the drivers of loss hiding behavior from an international setting, which in turn allows us to draw some broader conclusions about the banking sector beyond India. Our setting is particularly attractive in teasing out economic drivers of misreporting from the bank's investment decisions since much of the bad loans were made before the decision to reveal hidden losses was taken. Specifically, the regulator inspected the books of banks and uncovered instances of hidden losses for loans that were typically made years ago. Banks used various methods to hide losses such as changing the terms and conditions of loans made to a defaulting borrower to make it a "performing loan", extending new loans to pay for the old loans of borrowers close to default, and simply delaying the recognition of losses. As discussed in detail in Chari et al. (2019), in the aftermath of the global financial crisis RBI enacted forbearance measures to lower the capital requirement for borrowers with temporary liquidity issues. However, banks used some of the discretion provided by these measures to engage in zombie lending and hide losses, as revealed by the ex post audit that we study in the paper. RBI's supervisory audit uncovered these losses by inspecting the internal books of banks, comparing the loss recognition of the same borrower across banks, and evaluating the borrower's financial conditions based on

[4]We use NPLs (non-performing loans) and NPAs (non-performing assets) interchangeably in the paper to refer to corporate loans that were in default since the RBI's documents use the term NPAs for these loans.

public information.[5] Overall, using a standard methodology, the process ended up with a fairly detailed assessment of the extent of loan losses banks were hiding.

What could motivate a bank to hide its losses? Theoretical literature and institutional details provide two non-mutually exclusive motivations, one driven by shareholder-regulator conflict and the other by manager-shareholder conflict. By hiding their loan losses, banks' reported-profits become higher than the true profits and the reported level of risk lower than the true risk.[6] Together they can lower the bank's regulatory capital requirement, giving rise to the shareholder-regulator conflict. Such behavior is likely to be more prevalent when banks have lower equity capital or when they face a lower level of supervision from the regulators. We use bank capitalization, government ownership and representation of the regulator on the board of the bank as our main measures of shareholder-regulator conflict.

Additionally, managers can gain from the perception of better performance either directly through higher compensation or indirectly through a better labor market reputation. Thus managers are more likely to hide losses if their compensation depends on short-term reported performance, even if it destroys long-term value for the shareholders. Managerial myopia has been analyzed extensively in the literature (see e.g., Narayanan (1985), Stein (1989) and Von Thadden (1995)). Rajan (1994) develops a model in which short-sighted bank managers try to change the market's perception of true performance by inflating earnings or concealing losses, for example by continuing to lend to defaulters. In fact, Rajan (1994) emphasizes this agency problem can arise 'even if the bank is well capitalized'. This line of work suggests the importance of shareholder-manager conflicts in explaining the hiding behavior.

We measure shareholder-manager conflicts by the nature and composition of the shareholders of the bank. Our proxies are motivated by the basic idea that shareholders are less

[5] For example, the former Governor of the RBI, Prof. Raghuram Rajan states in his report to India's parliament:"Banks were simply not recognizing bad loans. They were not following uniform procedures – a loan that was non-performing in one bank was shown as performing in others. They were not making adequate provisions for loans that had stayed NPA for a long time. .... We proceeded to ensure in our bank inspections in 2015 that every bank followed the same norms on every stressed loan. We especially looked for signs of ever-greening. A dedicated team of supervisors ensured that the Asset Quality Review (AQR), completed in October 2015 and subsequently shared with banks, was fair and conducted without favor."

[6] Specifically, lower levels of non-performing loans mean lower loan loss provisioning, and hence higher profits.

likely to monitor when they are least informed about the true quality of a bank's lending portfolio, and when they are likely to reward the managers heavily for reported performance measures. The fraction of shares held by the foreign institutional shareholders (FIIs) provides a meaningful measure of this construct in our setting. These investors are likely to have less information about the quality of loan books compared to local investors such as domestic institutions and promoters. Some of these local investors, for example, have close ties with the borrowers of the bank through cross-holdings and other independent business relationships.

Distance as a metric of information asymmetry has been well studied in the broader banking literature (e.g., Stein (2002) and Petersen and Rajan (2002)). Distant monitors are more likely to rely on hard information such as reported NPL numbers, providing incentives and opportunities to the managers for hiding losses. Brennan and Cao (1997) show theoretically and empirically that FII portfolios are more responsive to public signals of information relative to their domestic counterparts.[7]

The FIIs' greater reliance on public information creates two reinforcing effects on manager's misreporting incentives: (a) they are less likely to be caught, and (b) their stock price, and hence compensation, is likely to be high with better publicly reported performance. Thus the potential punishment from misreporting comes down, whereas potential reward goes up. As a result, we expect increased hiding for banks with higher FII shareholding. This narrative, however, is not obvious. FIIs can bring in their superior governance technology to put pressure on underperforming managers, and improve governance in the domestic firm. Aggarwal et al. (2011) and Bena et al. (2017), for example, provide evidence that higher FII ownership boosts investment and governance of non-financial firms. Our empirical analysis is therefore of independent interest as well: whether the FIIs improve the disclosure practices of their portfolio banks in emerging markets or make it worse.[8]

While the FII shareholding is our key proxy for shareholder monitoring, we also analyze

[7]A number of papers have documented evidence of information disadvantage of foreign investors compared to local investors (see e.g., Kang and Stulz (1997))

[8]Boot and Macey (2003) highlight a fundamental trade-off inherent in any corporate governance mechanism: proximity versus objectivity. Proximity increases the information of the monitors, but proximate monitors can become too close to the management, losing the objectivity required for monitoring.

the effect of concentrated shareholdings and board monitoring on the hiding behavior as in the earlier literature on corporate governance. For board specific monitoring we use standard proxies from the literature such as the size of the board and the fraction of independent directors (e.g., see Adams and Mehran (2012)).

Our main sample covers all commercial banks in India for fiscal years 2016 and 2017, i.e., two years immediately after the new disclosure requirement consequent to the RBI's audit of the non-performing assets (NPAs) of commercial banks in 2015.[9] We find that one standard deviation increase in the FII's shareholding is related to a statistically significant 27.2% higher underreporting of the bank's gross NPLs. On the other hand, there is no meaningful relationship between the domestic financial institutions (DIIs) shareholdings and hidden losses. Thus, our results are not coming from institutional shareholding; rather, it is specific to distant, foreign shareholding, who are likely to possess relatively little information and therefore incur higher monitoring costs. Lending support to the monitoring based interpretation of our results, we show that hidden losses are higher when the FII shareholding is more dispersed. We find no meaningful relation between bank capitalization and board-level variables such as the independence of the board and the hiding behavior. The result is broadly consistent with the findings of Adams and Mehran (2012) in the context of the governance of the U.S. banks. Further, the effect of FII shareholding remains significant even after controlling for board level governance measures.

The FII shareholding is not randomly assigned, generating a genuine endogeneity concern with our study. What could be the alternative explanations behind our finding that links the FIIs to underreporting, if it is not our preferred monitoring-based explanation? A potential threat to our identification could be the hidden ability of the managers of the banks with high FII shareholdings. If banks with higher FII shareholdings have managers with poor ability to recognize losses in time, then our estimates may end up picking up that effect. We find this interpretation less plausible because the hidden losses arose mainly from the failure

[9]Most of the hidden losses became public during these two years right after the policy change, providing us with a clean setting to tease out the hiding behavior before the banks could change their lending or reporting decisions in response to the new regulation itself.

to recognize obvious cases of default, for example by rolling over the debt of a defaulting borrower.

To address the endogeneity concerns more directly and identify the monitoring channel, we make use of the fact that FIIs' investment in emerging markets is driven primarily by the inclusion (and weight) of a particular stock in popular Emerging Market Indices such as MSCI. Certain Indian banks are included in MSCI's India index, while others are not. We use the MSCI index inclusion as an instrument for the FII shareholding to identify the effect of the distant shareholders on the underreporting behavior. MSCI states that the inclusion of a stock in its index is mainly determined by factors such as liquidity, diversification benefits, and the market capitalization of the firm. We find a strong effect of FII shareholding on the underreporting of losses in the IV model using the MSCI index inclusion as the instrument while controlling for the index inclusion factors in the regression model.[10] Similar to Appel et al. (2016), our exclusion restriction relies on the idea that controlling for these factors, the inclusion of a bank in the index does not affect the underreporting except through its impact on the FII shareholdings. Further, we show that our instrument does not explain variation in the holdings of the domestic financial institutions (DIIs), proving further support to our claim that the inclusion in the MSCI index drives variation in FII's shareholding and not other institutional shareholding.

In the next set of tests, we establish a link between managerial incentives and misreporting in years leading up to the RBI's audit. In the first test, we investigate the effect of FII shareholding on the hiding behavior across the public-sector (i.e., majority government-owned) and the private-sector (i.e., not government-owned) banks of the country.[11] Private bank managers earn significantly higher compensation and a large part of their compensation is

[10] There is a large literature on the use of index inclusion as an instrument for active versus passive monitoring. A similar instrument is used in Aggarwal et al. (2011) and Bena et al. (2017). A closely related literature uses the inclusion of companies in the Russell 1000 index as an instrument (Boone and White, 2015; Appel et al., 2016; Schmidt and Fahlenbrach, 2017). This literature provides interesting insights into the nature and extent of governance exerted by passive funds. While our focus is different, our study contributes to that literature by bringing in a new dimension to passive investing in the international context: their reliance on hard information to reward managers who are distant.

[11] The majority-owner of a public-sector bank is the government of India, whereas the private-sector banks are primarily owned by non-government entities. Both types of banks in our sample are publicly traded and have FII investments in them.

performance-based.[12] Thus the private-public divide provides us with a natural variation in the extent of benefits managers derive from inflated short-term performance metrics. We show that private banks have higher misreporting, but it is the interaction of private banks with FII shareholding that provides the most meaningful variation in the hiding behavior. Within the set of private banks, one standard deviation higher FII shareholding is associated with about 39.4% higher misreporting. Within public sector banks, FII shareholding has no impact on misreporting.

Our results on private vs. public banks also allow us to comment on the importance of shareholder-manager conflict, holding fixed the shareholder-regulator conflict. Private-sector banks are likely to have similar incentives to exploit shareholder-regulator conflict. Our results show that within this set, the hiding behavior is present only when FII shareholdings is high. Therefore, for the same level of shareholder-regulator conflict, misreporting is present when monitor is distant, lending credence to our shareholder-manager based interpretation.

We directly assess the effect of managerial compensation on misreporting behavior in our next test by examining the effect of compensation policies across banks. Two results stand out. When CEOs' compensation is high, firms underreport more. Second, the effect of compensation on underreporting is considerably higher for banks with large FII shareholding. Overall these results paint a clear picture: diluted monitoring from distant shareholders combined with high compensation results in higher hiding.

To better understand the economic drivers of this behavior, we next investigate how banks responded to increased shareholdings by the FIIs in the years leading up to the regulation change. Using the panel of all bank-year observations from 2005 to 2015 and employing bank and year fixed-effects specification, we show that bank's reported profits go up and NPLs come down as the fraction of FII shareholdings goes up.[13] During the same time

[12] For example in 2015 the CEO of the largest private-sector bank, the ICICI Bank, earned 24.6 times higher compensation than the CEO of the largest public sector bank, namely the State Bank of India (SBI).

[13] Banks often disclose these measures as the key drivers of compensation for their top management. For example, while discussing the measures used to set compensation policy, ICICI bank in its annual report for 2017-18 states that: "The main performance metrics include profits, loan growth, deposit growth, risk metrics (such as quality of assets), compliance with regulatory norms, refinement of risk management processes and customer service. The specific metrics and weightages for various metrics vary with the role and level of the individual."

period, we show that CEO's compensation becomes more tightly linked to the reported NPL ratios for banks with higher FII shareholdings. This result is consistent with the idea that as the distance between the principal and agent increases, the principal is more likely to lean on hard pieces of information for decision making (see Stein (2002)). The FIIs rely on reported profitability and NPLs to evaluate the local managers, and the managers respond by providing better-than-actual NPLs.

These results paint a broad picture: performance-sensitive contracts may not be a complete substitute for the lack of monitoring. In fact, without proper monitoring, linking compensation to observable performance metrics can have a deleterious impact on the agent's behavior. U.S. institutions are known to deploy high powered performance-based incentive contracts in their firms (see Hartzell and Starks (2003)). Our study shows that the effectiveness of such a practice crucially depends on the information set of these institutions.

Our paper provides a first look at how shareholder monitoring and managerial incentives affect the hiding decision using precise data on hidden loans. We build on various streams of literature in finance and accounting. First, our work connects to the literature on the measurement and monitoring of risks in banks (e.g., see Behn et al. (2016), Begley et al. (2017), Bushman and Williams (2015) and Plosser and Santos (2014)). Second, our paper relates to the literature on shareholder monitoring (e.g., see the survey in Edmans and Holderness (2017)) and incentives to commit fraud. Using accounting restatements, Burns and Kedia (2006) show that option-based managerial incentives are positively related to incentives to misreport. Jayaraman and Milbourn (2015) underscore the importance of audit quality in this link. Povel et al. (2007) develop a theoretical model linking monitoring costs and misreporting incentives.

Our paper also contributes to the accounting literature on bank loan loss provisioning. Papers analyzing the determinants of loan loss provisioning, including Beatty et al. (1995), Ahmed et al. (1999), and Beatty et al. (2002) find evidence that banks use discretionary loan loss provisioning to meet earnings expectations and capital requirements. A more recent line of studies, including Beatty and Liao (2011), Bushman and Williams (2012), and Bushman and Williams (2015) have highlighted the importance of the quality of loan loss recognition for bank lending and risk-taking. We contribute to this literature by providing evidence that agency conflicts between shareholders and managers can encourage misreporting of accounting information about loan losses. An important distinction from the prior literature on loan losses is that our paper exploits variation in loan loss provisioning due to *misclassification* of accounting norms whereas previous work focuses almost exclusively on the variation in *discretion* in loan loss provisioning. Since our empirical setting uses a regulatory audit to uncover these misclassifications, an advantage of our paper is that we do not require a model-based estimate of loan loss recognitions.

We also contribute to the literature on the effect of investments by institutional investors, specifically foreign shareholders, on domestic firms (see e.g., Gillan and Starks (2007), Bena et al. (2017)). Our paper highlights a previously undocumented cost of FII investment: their reliance on (observable) performance-sensitive compensation contracts can facilitate untruthful reporting by the domestic firms.

Finally, our paper relates to the literature on the detection of zombie lending and its impact on the real economy (e.g., see Caballero et al. (2008)). Specifically in the Indian context, Kulkarni et al. (2019) study the build-up of credit to insolvent firms by Indian banks and its implication for the allocation of credit in the economy. Chari et al. (2019) investigate the role of regulatory forbearance on the buildup of zombie loans in India. Blattner et al. (2019) develop a measure of zombie lending for Portuguese banks to study the impact of a weak banking sector on productivity.

3.2 Indian Banking Sector and the Policy Change

The Indian banking sector is characterized by very large nation-wide banks that are either a private-sector bank or a public-sector one. In the public-sector banks, the Government of India is the majority, but not the only, shareholder. The private-sector banks have practically no direct government stakes. After the liberalization of the Indian economy in 1991, several regulations that earlier restricted shareholdings by foreign investors were relaxed. Over time, Foreign Institutional Investors (FIIs) have taken a considerable stake in Indian banks, both in the private-sector banks and the public-sector banks. Other prominent shareholder groups are "promoters", "domestic financial institutions", "corporate bodies", and "individuals". Promoters are either the Government of India for public sector banks or individuals for private sector banks. We provide descriptive statistics on the fraction of shares held by each of these groups later in the paper. Figure A.15 provides an example of the shareholding pattern for Yes Bank, a bank in our sample.

The largest public sector bank, the State Bank of India (SBI), has an asset base of 328 billion dollars as of 2015, whereas two of the largest private sector banks ICICI Bank and HDFC Bank have assets of 104 and 94 billion dollars, respectively on the same date. All three banks, as well as most other banks in the country, have branch networks across the country. Some banks specialize in regional markets, but even these banks are generally very large.

The issue of non-performing loans has been an important issue for market participants and regulators in India for a very long time. Chari et al. (2019) provide an excellent overview of the evolution of non-performing loans in India starting from the mid-2000s. Notably, banks used regulatory forbearance measures introduced during the 2008 financial crisis in order to 'avoid recognizing nonperforming loans' (Chari et al., 2019). Under this forbearance regime, banks would 'evergreen' and restructure loans to hide losses. In May 2013, the RBI announced that loan forbearance measures would come to an end in April 2015. As a follow-up, the RBI issued a Master Circular on July 1 2015 that introduced new norms on income recognition, asset classification and provisioning (IRACP). These measures aimed for more transparency recognition of and provisioning against non-performing loans.

Despite the withdrawal of forbearance, banks refused to recognize losses and 'when regulatory forbearance ended in April 2015, banks tried to find ways to keep accounts standard' (Dugal, 2017). Banks continued to evergreen and restructure loans despite new NPA classification rules which forbid classifying these loans as performing. This motivated Governor of RBI, Prof. Raguram Rajan to implement the first Asset Quality Review (AQR) by the RBI in mid-2015. This began the process for detection and better reporting of NPLs in the country. The goal of the AQR was to get banks to recognize losses that banks continued to hide from the prior forbearance regime. As a result of the AQR, the RBI found instances of 'divergences' in which banks incorrectly classified non-performing loans as performing under the IRACP norms introduced in July 2015.

In its monetary policy statement dated September 29, 2015, RBI explicitly discussed the issue of underreporting of NPLs and provisions: "As a part of its supervisory process, the Reserve Bank assesses compliance by banks with extant prudential norms on income recognition, asset classification and provisioning (IRACP). There have been divergences between banks and the supervisor as regards asset classification and provisioning. In order to bring in greater transparency, better discipline with respect to compliance with IRACP norms as well as to involve other stakeholders, the Reserve Bank will mandate disclosures in the notes to accounts to the financial statements of banks where such divergences exceed a specified threshold. Instructions in this regard are being issued separately."

[See Figure 3.1]

On April 18th, 2017, RBI mandated that banks report the divergence in their publicly reported NPLs and NPLs assessed by RBI as per its supervisory audit in a specified format if the extent of underreporting exceeds some threshold. As per the RBI's circular "In order to ensure greater transparency and promote better discipline with respect to compliance with IRACP norms, it has been decided that banks shall make suitable disclosures as per Annex, wherever either (a) the additional provisioning requirements assessed by RBI exceed 15 percent of the published net profits after tax for the reference period or (b) the additional Gross NPAs identified by RBI exceed 15 percent of the published incremental Gross NPAs for the reference period, or both." Thus banks that exceeded the 15% divergence level, as described above, were required to disclose the extent of divergence, called the NPA or NPL divergence, in their annual statements/financial results. RBI provided a very precise format to disclose these losses and we present one such example from Yes Bank in the Appendix to this chapter. We obtain our data from these public disclosures.

Banks began to report the extent of hidden losses starting from fiscal year 2015-16, and most of the underreporting were uncovered in the first two years after the new policy, i.e., in 2015-16 and 2016-17. We collect data from the financial statements of all Indian commercial banks for both 2015-16 and 2016-17 fiscal years for our main tests. In additional analyses, we also include the divergence data from 2017-18 and 2018-19. As expected, the level of divergence came down significantly in these two years since the banks had enough time to adapt to the new regime: the regulatory shock uncovered a large number of hidden losses soon after the RBI audit, providing us with an excellent setting to analyze their economic drivers in the immediate aftermath of the policy change.

While we do not have access to the precise data and methodology used by RBI to detect the divergence, some general principles are well known. In general, a loan is divergent if it is misclassified according to RBI IRACP norms for non-performing loans[14]. In its initial AQR conducted in 2015, the RBI focused on issues such restructured loans where original terms of the loans were modified to avoid classifying a bank as an NPLs. For example, a bank can delay classifying a loan as a bad loan by continuing to lending to a defaulting borrower, i.e., by ever-greening the loan, sometimes called the 'extend and pretend' policy.[15]

Second, if a loan to the same corporate borrower was classified as NPL by one bank, other banks with similar loan terms were required to classify their loans as NPLs as well. For example, under IRACP norms at the time a bank must classify a loan as non-performing if the payment was late by 90 days or more. In 2015, Essar Steel took 92 days to make payment to a syndicated loan. While HDFC bank and Bank of India classified this account as non-performing, ICICI bank and State Bank of India classified it as performing (Nair and Sanjai, 2015). Overall, the entire effort was geared towards cleaning up the accounts of India's bank, a policy initiative undertaken by the then governor of the bank.

[14]The July 2015 IRACP norms are available at https://www.rbi.org.in/Scripts/BS_ViewMasCirculardetails.aspx?id=9908

[15]As per RBI's Deputy Governor Mr. N.S. Vishwanathan's address to the industry practitioners on August 30, 2016: "During the five years to March 2015, banks have resorted to restructuring of loans in many cases to postpone recognition of non-performance, or what we now call 'extend and pretend', rather than using it as a tool to preserve the economic value of the units as intended. As a result, until 2016 the restructured assets constituted more than 50% of the stressed assets of all scheduled commercial banks masking the actual extent of deterioration of the loan portfolios...."

While the issue of the build-up of hidden loans was debated for some time (see Chari et al. (2019)), it was not clear whether the RBI or the government will indeed conduct such an audit, let alone disclose the results publicly. The consequences of such misreporting for the top managers of the banks were also not clear. For example, no CEO of the top bank of the country was punished for the suspicion of hiding losses before the RBI's audit. Market observers attributed the changes in the RBI's policy largely to the change in its top leadership. Even from the market's perspective, the extent of NPL divergence was not completely anticipated. The second column of Figure 3.2 presents the average return around a window of 5 days of the announcement of NPL divergence by the banks in the first year of reporting. The divergent banks had a negative abnormal return of -6%, compared to +1% return for banks that did not report any divergence. In contrast, when it was announced that divergences were found in September 2015 (but before the divergence reports were publicly disclosed), banks that were later revealed to have divergences experienced a positive +1% return while non-divergent banks had a near 0% return. In sum, the regime change in the RBI's audit policy provides us with a setting where the lending decisions were made under the assumption of partial or no knowledge of the detection of hidden losses and the economic consequences that followed.

[See Figure 3.2]

3.3 Data and Sample

We collect data from three primary sources: annual reports of banks during 2016 and 2017, RBI's statistics on Indian Banks, and Prowess database. Data on misreporting comes from the annual reports. As discussed earlier banks were required to report both the extent of hidden NPLs and the resulting underreporting of loan loss provisions as a note to the shareholders if such losses exceeded a certain threshold. Data on financial conditions of banks and shareholding patterns come from RBI and Prowess.

Our sample covers all scheduled commercial banks of India that were required to report NPA divergence in their annual report. This covers practically the entire banking sector in the country. The only significant group that we miss from this sample is foreign banks operating in India. This group has only a minor market share in the country. Our main test linking NPL underreporting to FII shareholding is based on fiscal year 2016 and 2017 data. In total, we have 73 bank-year observations covering 37 distinct banks. Of this sample, 53 observations are for bank-years that reported NPA divergence, i.e., for these banks the extent of underreporting exceeded the 15% threshold criteria in the year. In our regression analysis, we use both an ordinary linear regression analysis and Tobit model to tease out the economic drivers of hiding.

It is worth emphasizing that the relatively smaller sample size presents some challenges in terms of the power of the tests. However, since we have the entire population of banks in India, our analysis does not have any sample selection concerns. In addition to the NPL divergence test, we also investigate the relationship between FII shareholding and the firm's performance over 2005-2015 period to understand the dynamics of firm behavior and remuneration in response to FII shareholding. These results are based on the sample of all private and public sector banks during this period, with a panel of 377 bank-year observations.

3.3 Descriptive Statistics

Table 3.1 provides summary statistics of key variables used in our study broken down into two periods: (i) 2016 & 2017, i.e., the main sample for our tests on NPL hiding (Panel A), and (ii) 2005-2015 period based on which we investigate firm performance and CEO remuneration in periods leading up to the policy change on disclosure of the NPLs (Panel B).

[See Table 3.1]

As shown in Panel A, the extent of underreporting has been quite large. Out of 37 banks in the sample, 32 reported divergence at least once. Thus 86% of banks exceeded the 15% threshold for reporting requirements at least in one of these two years. Of the reporters, the average firms underreported 23% of its NPL and 18.5% of provisions. Figure 3.3 demonstrates the magnitude of underreporting on a yearly basis.

[See Figure 3.3]

To put it in the aggregate context, during these two years banks in our sample reported aggregate profits of 9.2 billion dollars before the detection of underreporting. Once we account for the underreporting, 58% of these reported profits disappear due to additional loan loss provisions the banks were required to make on account of underreporting. In terms of aggregate NPLs, the banking sector as a whole underreported (gross) NPL of 20 billion dollars which is 172% of the reported incremental (gross) NPL during these two years. Thus our setting is economically very meaningful. Indeed, there has been an intense debate in the regulatory as well as the investment community in India about these NPL divergences and its implication for financial stability and bank lending.

Contrasting the profitability numbers in Panel A and B, it is clear that the banking sector reported much better performance during 2005-2015 period, and was under stress in 2016-2017 even before accounting for the hidden losses. Indian economy grew at an average annual growth rate of 7.73% during 2005-2015, and the banking sector grew with it. However, as pointed out earlier banks made significant amounts of bad loans during this period that started to reflect in their balance sheet in the later parts of this period.

Panel A also provides the summary statistics of our key explanatory variables. Institutional investors – domestic and foreign combined – hold about 32% of shares in banks, with FIIs holding about half (16%). Table 3.2 provides a more detailed breakdown of the shareholding structure across different classes of shareholders. Broadly they can be divided into three groups: promoters, institutions, and non-institutions. Promoters are the initial sponsors of these banks. For public sector banks, it is the government of India, whereas for private banks typically the promoter is an individual or a family. The median number for promoter holding is 61% because the government holds the majority stake in the public sector banks. More important for us, there is a large cross-sectional variation, both within private and public banks, along these dimensions. FII shareholding ranges from 3.43% at the 25th percentile to 24.5% at the 75th percentiles. We exploit these variations in our tests.

[See Table 3.2]

3.4 Results

Our primary test uses an ordinary linear regression model for the subset of banks that disclose positive values of NPL divergence. The dependent variable is the log ratio of actual NPL to the reported NPL at the bank-year level. Since banks were required to disclose the amount of NPL divergence only if it exceeded a certain threshold, we also complement the linear regression model with a Tobit model.[16] As discussed earlier, the value of the reporting threshold was bank-specific, 15% of incremental NPL of the bank during the year. Hence we need to transform these variables to ensure that the left censoring occurs at the same point for every bank. We do so by transforming the NPL numbers in the following manner: (Actual NPL - Reporting Threshold)/Reported NPL. For a bank that falls just at the reporting threshold, the reported NPL equals the difference between the actual NPL and the threshold value, i.e., the transformed value for such a bank equals one.[17] We then take the log transform of this variable to construct our dependent variable for the Tobit regression. With the log transformed values, the left censoring occurs at zero for each bank. We provide an example of this construction method in Appendix Table A.18.

We first present the extent of underreporting by banks that exceeded the reporting threshold across different quintiles of FII shareholdings, measured at the end of 2015 fiscal year. The results are presented in Figure 3.4. A remarkable pattern emerges from this plot. For the first three quintiles of FII shareholding, which works out to shareholdings of less than 9.48%, the extent of underreporting is much lower compared to the top two quintiles. The positive relationship between FII shareholding and underreporting is almost monotonic. Compared to the lowest FII shareholding quintile, banks in the highest quintile have 58% higher underreporting.

[See Figure 3.4]

[16] We also present the estimation results from an alternative econometric approach: interval regression in Appendix Table A.20.

[17] The disclosure requirement has two criteria. We construct the censored variable based only on one of the two criteria, the primary one: i.e., the divergence is above 15% of incremental NPA. The other criteria, namely the divergence exceeding 15% of net profits, complicates the economic interpretation because some banks have negative profits. This choice has only a minor impact on our analysis and inference.

Table 3.3 presents the regression results that account for the size and capital position of the bank, as well as an indicator variable that captures the year fixed effect, i.e., whether the underreporting is from fiscal year 2016 or 2017[18]. Panel A presents the OLS regression results for the set of banks that exceeded the 15% threshold. As seen in Column (1), increased FII shareholding is associated with significantly higher hiding of losses. For the ease of exposition, we standardize all explanatory variables by subtracting the respective mean and dividing the difference by the standard deviation of the variable[19]. Thus all estimates represent the effect of one s.d. change in X-variable on the Y-variable. One s.d. change in FII shareholding is associated with 27.2% higher underreporting. There is no meaningful relationship between the capital position of the bank, our key proxy for the shareholder-regulator conflict, and the hiding behavior.

[See Table 3.3]

Columns (2)-(3) show that it is only the FII shareholding, and not the domestic institutional shareholding, that is driving our results. For example, compared to Column (1) that uses FII shareholding as the main explanatory variable, in Column (2) that instead uses DII shareholding, the R^2 of the model drops from 46% to 21%; while the coefficient is highly significant for FII, the estimate on DII is statistically zero. Hence our results point to a special effect of foreign investors, and not simply institutional investors.

Panel B uses the entire sample, including banks that were below the underreporting threshold, in a Tobit framework[20]. One s.d. higher FII shareholding is associated with about 35.6% higher underreporting, and the result is significant at 5% level. The economic magnitude is in line with the OLS estimates discussed earlier.

In our next test, we investigate whether the concentration of FII shareholding matters for hidden losses. Concentrated holdings by shareholders are likely to increase the benefits of monitoring. When there are fewer FII shareholders for the same level of total shareholdings,

[18] We measure FII shareholding and other explanatory variables in 2015, before the underreporting was disclosed.

[19] The only exception is indicator explanatory variables.

[20] Results using Interval Regression are similar and reported in the Appendix to this chapter.

the monitoring is likely to be higher. In order to capture this effect, we create a variable $\frac{1}{No.\ FII}$ that measures the inverse of the number of FIIs present in a bank, i.e., a measure of concentrated shareholding. We interact this variable with total FII shareholding to assess whether the positive effect of FII shareholding on the hiding behavior changes when the shareholders are less dispersed.

[See Table 3.4]

Results are provided in Table 3.4. We find a negative and significant coefficient on the interaction of FII shareholding and our concentration measure ($\frac{1}{No.\ FII}$). Further, the independent effect of total FII shareholding is even higher compared in this model that includes the interaction term: one s.d. increase in FII shareholding is associated with 35% higher hiding in this model compared to the corresponding estimate of 27% in the model that does not control for the interaction effect. Overall, these results show that banks hide more when their shareholders are distant and dispersed. As shown in Panel B of the Table, the Tobit estimates are even stronger.

Other monitoring devices: In our next set of tests, we focus on board monitoring using a number of proxies for this variable based on prior literature. Results are provided in Table 3.5. We find that board size, the duality of CEO and the chairman role, and the fraction of board outsiders do not significantly explain variation in bank hiding. We do find some evidence of regulatory monitoring on the board: banks with RBI members on the board are associated with 28.3% less underreporting. In Column (6), we include all board monitoring variables in one specification. Only RBI membership is significantly associated with bank hiding at the 5% level. We introduce FII shareholding to the model in Column (7), and its coefficient is still positive, significant, and very close in magnitude to the original estimate. A clear pattern emerges from these findings: FII shareholding is one of the key drivers of loss hiding behavior, with board monitoring having little-to-no impact.

[See Table 3.5]

3.4 Instrumental Variable Regressions

A key concern with our interpretation that lack of monitoring by FIIs causes hiding behavior is that it is not the FII's shareholding but some omitted variable that drives both the FII's shareholding and hiding behavior. What could potentially be these omitted variables that explain the variation in FII shareholding and loss hiding at the same time? One natural candidate is the hidden governance characteristics that attract higher FII shareholding and at the same time also incentivize untruthful reporting. As per this alternative, FIIs invest in firms with poor governance characteristics and our estimate simply captures that correlation. This alternative explanation does not seem plausible based on earlier work that shows that FIIs are more likely to invest in firms with better governance on other observable dimensions. Hence the direction of bias should go against our findings. Further, we control for several governance variables such as board size and independence and show that the relation between FII shareholding and underreporting does not get explained by these variables.

However, if banks with higher FII shareholding are simply bad at assessing the extent of NPLs they have, then our results could be due to the hidden ability to understand NPLs. Could our results be driven by this force? We address this more directly by using an interesting driver of FII shareholding in a firm: its inclusion in broadly tracked MSCI index. The MSCI emerging market has a considerable influence on how an FII picks a stock within a country. The index provides weights based on the country, sector, and firms within the sector to provide a well-diversified benchmark to foreign investors. The inclusion is based on a number of factors, the most important of them being the size of the market capitalization, float-adjusted market capitalization, liquidity (as measured by trade volume), fraction of shares available to foreign investors (greater than 15%), and minimum trading time. When the index changes the weights of a country or a particular stock in the country, the FII's investments in the company changes too. For example, in May 2019, the MSIC emerging market index increased its weight on Chinese Class A shares, a move that may have resulted in an outflow of almost $1 billion from the Indian markets as per some analysts.[21]

[21]See https://economictimes.indiatimes.com/markets/stocks/news/msci-rejig-may-lead-to-1-billion-fii-

Motivated by these features of the index and its impact on FII's shareholding in a firm, we use the inclusion of a bank in the index as an instrument for our IV regression. The instrument, $MSCI$, is equal to 1 if the bank's stock is included in the MSCI India domestic index in May 2015 and 0 otherwise.[22] The banks in the index at this time were HDFC bank, ICICI Bank, Kotak Bank, Axis Bank, State Bank of India, IndusInd Bank, Yes Bank, and Bank of Baroda. Note that the index includes both private and public sector banks.

The exclusion restriction relies on the assumption that the inclusion in MSCI index is not influenced by omitted variables of concern such as the hidden ability of the managers to understand and account for the true levels of NPLs. This is a plausible assumption since indices such as MSCI are often designed to capture the diversification benefit these stocks provide to an international investor and the fact that change in weight depends on a host of factors including the changes in weight across countries, sectors, and companies. A similar instrument is used in

[See Table 3.6]

We provide the IV estimation results in Table 3.6. Panel A produces the OLS estimates, Panel B Tobit. We document the first stage regression results, the reduced form results, and finally, the second stage results in both panels. We focus on the model specification that includes the index inclusion criteria in addition to our instrument: the indicator variable for index inclusion. As shown in Column (2) of Panel A our instrument is strong in the sense of statistical relevance. Inclusion in MSCI index is associated with 1.31 standard deviations or 18.68% higher holding by the FIIs. The first stage F-statistic for the excluded instrument is about 10 and the R^2 of the model is 82%: we have a strong, relevant instrument. Figure 3.5 shows the relevance of this instrument graphically by plotting the average FII shareholdings across three groups: banks included in the MSCI index, non-included private banks, and non-included public banks. Clearly, MSCI inclusion strongly affects the extent of FII shareholdings in a bank.

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outflow-from-india/articleshow/69321966.cms?from=mdr

[22]The same set of banks in the index was constant through November 2016

[See Figure 3.5]

The reduced form estimate linking underreporting to the instrument directly shows that banks that were included in the MSCI index underreported 75.9% higher NPLs. As we mentioned earlier, MSCI index included both private-sector and public-sector banks. These banks collectively underreported significantly higher amounts of NPLs compared to all other banks. In fact, comparing MSCI included banks with the rest of public and private-sector banks, we find that it is the MSCI subsample that underreported the maximum amount of NPLs. MSCI group underreported by 64.6%, compared to 21.6% for the remaining private sector banks and 9.2% for the remaining public sector banks as shown in Figure 3.6. Column (6) produces the second stage IV estimates: one s.d. higher FII shareholdings is associated with about 57.8% higher underreporting. The effect is statistically significant at 1%. Compared to the corresponding OLS estimate of 27%, IV estimates are slightly higher. IV estimates are also larger after controlling for determinants of index inclusion: market capitalization, float-adjusted market capitalization, liquidity, and foreign room. This is consistent with our earlier argument that active investment by the FIIs target firms that are better at governance, hence the selection bias should go against our findings. When we tease out the variation that comes from passive index based investing, we more likely recover the portion of non-information based investing and our results become slightly stronger in economic terms.

[See Figure 3.6]

3.4 Private-sector vs. Public-sector Banks

We investigate the effect of private-sector versus public-sector banks with two key motivations. First, we want to investigate if our results are simply driven by the government's stake in the bank instead of distant monitors. Second, private-sector banks have much stronger incentive based compensation contracts compared to their public-sector counterparts. Hence this test allows us to see whether our results are driven by banks whose managers stand to gain more from underreporting.

[See Table 3.7]

Table 3.7 documents the results. For expositional simplicity, we reproduce the estimates linking FII shareholding and underreporting in Column (1). Column (2) shows that private banks had a much higher level of underreporting, both based on OLS estimates (Panel A) and Tobit estimates (Panel B). Private banks have about 57% higher underreporting conditional on reporting their NPA divergence (Panel A). Notice the model fit of Column (1) versus Column (2). FII shareholding explains larger variation in underreporting (R^2 of 46%) than the private-public divide (R^2 of 34%). The key estimates are contained in Column (4) that includes both these variables – FII and Private – along with their interaction term. In the OLS model, the interaction term is positive and significant, whereas the individual effects are statistically insignificant. Thus the higher level of underreporting is concentrated within private banks with high FII shareholdings. The interaction term is positive and significant in the Tobit model as well. As expected, there is a high positive correlation between FII and Private (0.8676 correlation coefficient). However, even within the set of private banks as the FII shareholding increased banks underreport more. Thus our results linking FII to underreporting are not simply explained away by the private-public divide. This points to the importance of the shareholder-manager conflict driving the results as opposed to the shareholder-regulator conflict. We explore the second possibility that it is the compensation-based incentives of private sector banks that are driving our result in our next test.

3.4 Compensation

We gather data on the total remuneration of the CEOs of all the banks in our sample. First, we hand collect the names of each bank's CEO's over the period 2005-2017. Second, we merge this information with the board of directors data in Prowess, which provides information on total remuneration. We begin our analysis with some univariate results. In Figure 3.7, we plot the average underreporting by banks that fall in different quintiles based on the remuneration of the CEO. The relationship is stark. As CEO compensation increases, the extent of misreporting increases in a monotonic fashion as well. Compared to the lowest paid CEO quintile, the higher paid CEO's bank has 65% higher misreporting. Observations in the top two quintiles are all private sector banks.

[See Figure 3.7]

Regression results are provided in Table 3.8. Banks with highly compensated CEOs underreport more. One standard deviation higher compensation is associated with about 26% higher underreporting (Column 1). As shown in Column (2), the interaction term between FII shareholding and remuneration is positive and significant. The finding shows that banks with larger FII shareholding and large remuneration are the ones that underreport more. This result is a more direct version of our earlier result where we show that FII shareholding in private banks is the main driving force behind our results. However, the remuneration based test allows us to establish the economic channel more precisely: it captures the variation in compensation across banks and shows that when CEOs stand to gain more they hide more.

[See Table 3.8]

3.4 Historical Performance

We now look at how CEOs were compensated for their performance during 2005-2015, i.e., during a period when the disclosure policy was relatively less truthful, to gain further insight into the relationship between compensation contract linked to hard information and misreporting behavior. We proceed in two steps to do so. We first investigate whether banks reported better performance as FIIs increased their shareholdings. Subsequently, we investigate whether the CEOs were rewarded more for improved performance. Together, these tests allow us to link increased FII shareholding to improved hard performance and managerial incentives to hide losses.

In Table 3.9, we estimate the following model linking FII shareholdings to reported performance:

$$perf_{it} = \alpha_i + year_t + \beta \times FII_{it} + \epsilon_{it} \tag{3.1}$$

$perf_{it}$ measures bank i's performance in year t, and $FIII_{it}$ is the percentage shareholding of the FIIs in that bank-year. The model includes both bank and year fixed-effects to soak away yearly variation in the performance of the banking sector as well as bank specific differences in performance. We use three measures of performance: the ratio of NPLs to total assets, the profitability of the bank as measured by its net profits scaled by total assets, and the level of outstanding loans. The model is estimated with 377 bank-year observations from 2005 to 2015, i.e., using information from the period before the RBI's regulation change.

[See Table 3.9]

A clear pattern emerges. As FII shareholdings increase, banks report lower levels of NPLs (Column 1), higher profitability (Column 2), and higher growth in the lending portfolio (Column 3). A one s.d. increase in FII is associated with a 0.686% lower NPL-to-Asset ratio, 0.178% higher net profit ratio, and 15.6% more loans. Thus, FII shareholding is associated with high growth and profits, all with lower NPLs. Given our earlier results on underreporting, clearly some of this better reported performance came from hiding of the losses, rather than more prudent lending decisions. Did the CEOs benefit from this? We answer this question by investigating how CEOs were compensated during this period. We regress their (log of) annual compensation on performance metrics, including NPLs, to assess how tightly their compensation is linked to observable, reported performance metrics. Results are provided in Table 3.10.

We first provide a regression of compensation on key performance metrics: profitability, NPL ratio, growth rate, and asset size on the entire sample. The model includes bank and year fixed effects. CEOs get compensated more when their banks show lower NPLs. The economic magnitude of NPL is highly significant. A one s.d. lower NPL ratio (or a 3.53 drop in NPL ratio) is associated with 26.2% higher CEO compensation. The model as a whole explains a reasonable portion of variation across bank CEO's compensation with an overall R^2 of 86% and within-bank R^2 of 6%. Next, we break our sample into two groups: high and low FII shareholding based on the median value of the average of each banks' FII shareholding over the entire sample. A clear pattern emerges: these performance metrics explain a significantly higher fraction of variation in CEO compensation when FII shareholding is high: overall and within R^2 of 91% and 13%, respectively. In contracts for low FII shareholding banks, the corresponding R^2 are much lower at 40% and 1%. These results show that FIIs depend more on reported performance metrics, especially the levels of NPLs, in setting the CEO's compensation contract. As shown in Columns (2) and (3) of the Table, for the higher FII shareholding group, one s.d. lower NPLs is associated with 27.0% increase in the CEO's compensation, whereas the corresponding number is a statistically insignificant 5.5% for the lower FII shareholding group. Thus banks with higher FII shareholding link their CEO's compensation much more tightly with these observable metrics, especially with the level of NPLs.

We explore this analysis further by estimating the following model with both the high and low FII shareholding groups together. This analysis allows us to pin down the compensation-NPL relationship as a function of the level of FII shareholding and complements the results presented above that estimate this relationship separately for the two groups.

$$comp_{it} = \alpha_i + year_t + \beta \times NPL_{it} + \gamma \times FII_{it} + \theta \times FII_{it} \times NPL_{it} + \epsilon_{it} \tag{3.2}$$

As shown in Column (4), there is a negative and significant coefficient on the interaction term (coefficient θ in the regression above), indicating that as FII shareholding increases, the CEO's compensation becomes more sensitive to the reported levels of NPLs. Column (5) supplements this analysis by showing that the CEOs of banks with higher FII shareholding were paid more. Combined with the estimates of Column (4), it is clear that the lower levels of NPLs contributed significantly to the higher compensation of these CEOs.

Together these results show that distant monitors rely more on observable metrics to compensate their managers. This is consistent with a model such as

3.4 Manager-Shareholder Alignment

One alternative interpretation of the results is that foreign investors encouraged managers to hide their losses. In this view, foreign institutional investors are more informed than other shareholders. If managers hide losses, informed shareholders can benefit from uninformed shareholders' positive reception of inflated accounting numbers via higher stock prices. For this story to hold, informed investors must undo their positions in the banks' stocks prior to the public disclosure of underreported losses. That is, informed shareholders can only benefit in the short-run.

The evidence, however, is not consistent with this explanation. As shown in the IV regressions, FII positions in banks stocks are driven by investors who follow a passive indexing strategy. Such a passive strategy is inconsistent with closing positions in banks predicted to have hidden losses revealed by an auditor in the near future. We additionally provide two pieces of evidence to support this conclusion. First, a unique feature of our empirical setting is that the RBI announced that it found hidden losses in September 2015 but did not release the results of individual banks to the public until May 2017. If informed shareholders knew which banks were hiding losses, then we would expect to see negative stock market returns for those banks in September 2015. Figure 3.2 shows that this is not the case. In fact, banks that were later revealed to have hidden losses experienced positive abnormal returns upon this announcement. This is inconsistent with the presence of any informed shareholders aware of managers hiding losses at specific banks.

[See Figure 3.2]

Second, in order for FII to gain from private information about banks hidden losses, they must close their positions prior to the public revelation of those losses. Figure 3.8 plots the average FII holdings for divergent and non-divergent banks and provides evidence that does not support this implication. Rather, the patterns in FII shareholding for divergent and non-divergent banks remains nearly parallel even after the RBI announcement of the hidden losses in September 2015. The lack of any meaningful change in FII position indicates FII were unaware of which banks had hidden losses and therefore unable to profit from such a strategy.

3.4 Robustness Tests

We conduct a series of robustness checks to provide further support to our main claim that distant monitors coupled with performance-linked compensation contracts are the key driver of our findings. First, we re-run our earlier tests using a set of richer control variables. Our base tests so far controlled for the firm's capitalization ratio, size, and year fixed effects. Now we include additional variables such as asset growth and the level of GNPA scaled by total assets in the model. The asset growth rate accounts for the investment opportunities of the bank, whereas the level of GNPA captures the quality of the investment portfolio itself. Table A.21 in Appendix D presents these results. Our main results remain the same.

3.4 IV Placebo

Clearly, we cannot test the exclusion restriction of our instrument, MSCI index inclusion. However, we can rule out any mechanical relationship between the instrument and underreporting using a placebo test in the following manner: we use MSCI inclusion as an instrument for DII shareholdings. This placebo test allows us to comment on whether our instrument is picking up variation in institutional holding rather than distant monitors. We regress DII shareholding on the MSCI instrument in Table A.22 in Appendix D using the same first stage specification as in our actual IV test. As expected, the coefficient is not statistically different from zero and has a very small t statistic. Furthermore, the F statistic is small and less than 1 in all specifications.

This result is useful because it shows the instrument works intuitively: MSCI index inclusion only attracts FII but not DII investment. DII shareholders, whom we have shown to be better monitors, are unaffected by MSCI inclusion. Therefore, we can at least rule out that MSCI inclusion is related to DII investors with preferences for banks with lower NPL underreporting.

3.5 Conclusion

We show that managers are more likely to hide losses, and thus inflate short term profits when their shareholders are distant. Distance amplifies information frictions and hinders the shareholders' ability to properly monitor the managers. Thus managers are able to engage in misreporting without facing any significant probability of getting caught. When they stand to gain from inflated performance measures, misreporting incentives go up as well. At a very broad level, our paper shows that distant monitors should use caution in relying on performance-linked compensation contracts as a substitute for monitoring: it can make the problem worse by providing the managers an incentive to engage in untruthful reporting.

3.6 Tables and Figures

TABLE 3.1. Summary Statistics

Table 3.1 contains summary statistics for the banks in our sample. Panel A reports measures in 2016 and 2017 during which we observe banks underreporting. Panel B reports summary statistics over the historical period 2005-2015. $GNPAUR$ and $ProvisionUR$ are the amounts of GNPA and Provisions underreporting scaled by total assets. $Capital$ is the Tier 1 Capital Ratio. $\%Inst$ and $\%FII$ are the percentages of bank equity owned by institutional and foreign institutional investors. $\frac{\%FII}{No.\ FII}$ is the average shareholding by FII. $\%RBI$ is the percentage of bank equity owned by RBI. $RBI\ Mem$ is an indicator equal to 1 if board member represents the RBI. $Board\ Size$ is the number of board members. $CEOChair$ is an indicator equal to 1 if the chair is also the CEO of the Bank. $\%Outsiders$ and $\%Audit\ Board\ Outsiders$ are the fraction of board and audit board members who are outsiders to the bank. $GNPA$ is the amount of gross non-performing assets scaled by total assets. $Provisions$ are the amount of provisions for gross non-performing assets in millions of dollars. $NetProfit$ is net profits after taxes in millions of dollars. $Total\ Assets$ is total assets in millions of dollars. $Remun.$ is the amount of total remuneration awarded to the bank's CEO in dollars. Lev is total debt plus total deposits divided by total assets. $TobinQ$ is bank book value divided by market value of bank. ROE and ROA are the bank's return on equity and return on assets in that fiscal year. All variables are measured at the end of a bank's fiscal year.

Panel A: Observed Underreporting Period: 2016-2017

	N	Mean	SD	P10	P25	P50	P75	P90
$GNPA\ UR$	53	23.022	34.445	3.103	5.913	11.988	24.219	53.359
$Provision\ UR$	53	18.477	22.272	2.849	4.944	10.058	20.570	44.899
$Capital$	73	9.907	2.808	7.520	8.020	9.050	11.260	14.210
$\%Inst.$	73	31.853	18.983	13.640	17.780	25.940	41.760	61.390
$\%FII$	73	16.101	14.257	1.500	3.430	11.720	24.520	39.710
$\frac{\%FII}{No.\ FII}$	73	0.122	0.208	0.021	0.036	0.055	0.124	0.245
$\%RBI$	73	40.949	35.793	0.000	0.000	61.255	70.760	80.985
$RBI\ Mem.$	73	0.575	0.498	0.000	0.000	1.000	1.000	1.000
$Board\ Size$	72	14.417	2.336	12.000	13.000	14.000	16.000	18.000
$CEO\ Chair$	73	0.466	0.502	0.000	0.000	0.000	1.000	1.000
$\%Outsiders$	73	29.455	26.021	0.000	0.000	30.000	50.000	66.667
$\%Audit\ Board\ Outsiders$	73	39.448	36.672	0.000	0.000	33.333	66.667	100.000
$GNPA$	73	0.050	0.032	0.010	0.018	0.045	0.073	0.087
$Provisions$	72	1041.093	1223.588	41.508	100.409	577.698	1572.829	2969.109
$Net\ Profit$	73	126.471	571.781	-422.730	-131.163	54.449	171.374	558.192
$Total\ Assets$	73	49749	65569	5357	15306	32622	56085	105405
$Remun.$	61	274434	406606	21589	33243	47709	176314	881708

Panel B: Historical Period: 2005-2015

	N	Mean	SD	P10	P25	P50	P75	P90
$Capital$	377	10.090	2.567	7.520	8.050	9.300	11.500	14.210
$\%Inst.$	377	28.432	14.539	10.640	18.320	26.880	35.850	49.010
$\%FII$	377	16.894	14.075	1.740	3.770	11.820	27.910	39.710
$Lev.$	377	0.896	0.032	0.847	0.882	0.906	0.917	0.924
$TobinQ.$	377	1.073	0.129	0.995	1.017	1.044	1.085	1.166
ROA	377	0.951	0.554	0.330	0.640	0.980	1.330	1.610
ROE	377	14.032	7.763	5.717	9.843	14.796	19.124	22.032
$GNPA$	375	0.018	0.010	0.007	0.010	0.015	0.023	0.033
$Provisions$	375	313.327	597.595	16.647	53.046	128.086	347.793	658.646
$Net\ Profit$	377	272.820	393.401	16.416	61.745	139.727	290.628	734.619
$Total\ Assets$	377	31745	42765	2542	7608	18229	37728	76413
$Remun.$	277	192103	295163	9224	28531	52022	184141	656307

TABLE 3.2. Shareholding Composition

Table 3.2 contain summary statistics for shareholder ownership of banks during 2016 and 2017 when we observe underreporting. Promoters, Institutions, and Non-Institutions roughly make up 100% of bank ownership. Indented variables break down these amounts into finer categories. $\%IndianProm.$ and $\%ForeignProm.$ are the percentages of bank equity owned by Indian and Foreign Promoters .$\%FII$ and $\%DII$ are the percentages of bank equity owned by foreign and domestic institutional investors. $\%Mutual\ Fund$, $\%Insurance$, and $\%Bank$ are the percentage of bank equity owned by domestic mutual funds, insurance funds, and banks. These are a subcategory of $\%DII$. $\%Corp.$ is the percentage of bank equity owned by non-promoter corporate bodies. $\%Individuals$ is percentage of bank equity owned by non-promoter individuals. All variables are measured at the end of a bank's fiscal year.

	N	Mean	SD	P25	P50	P75
<u>Promoters</u>	73	46.829	30.246	16.720	61.260	70.760
$\%Indian\ Prom.$	70	47.918	30.487	20.190	61.350	72.830
$\%Foreign\ Prom.$	63	1.020	3.951	0.000	0.000	0.000
<u>Institutions</u>	73	31.853	18.983	17.780	25.940	41.760
$\%FII$	73	16.101	14.257	3.430	11.720	24.520
$\%DII$	73	14.539	7.026	9.730	13.850	18.720
$\%Domestic\ Mutual\ Fund$	73	5.602	6.163	0.040	4.380	9.520
$\%Domestic\ Insurance$	73	8.268	6.704	1.430	10.140	14.100
$\%Domestic\ Banks$	73	1.748	3.513	0.110	0.210	1.700
<u>Non-Institutions</u>	73	21.201	21.628	7.400	11.520	21.510
$\%Corp.\ Bodies$	73	3.807	5.145	0.820	1.510	5.380
$\%Individuals$	73	15.352	15.914	6.010	8.350	13.330

TABLE 3.3. Shareholder Monitoring

OLS Dependent variable is log(Actual NPL/Reported NPL). In the Tobit panel, the dependent variable is log of (Actual NPL - 0.15 x Incremental NPL)/Reported NPL. $\%FII$ and $\%DII$ are the percentages of bank equity owned by foreign and domestic institutional investors. *Capital* is the Tier 1 Capital Ratio. All explanatory variables are measured in 2015 (prior to underreporting disclosures). All explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Panel A is estimated via OLS for the sample of banks we observe reporting divergences. Panel B contains results from a Tobit regression using the sample of all banks in 2016 and 2017. Observations are censored below by the 15% minimum GNPA required to report. Standard errors are clustered at the bank level.

Panel A: OLS

	(1)	(2)	(3)
$\%FII$	0.272**		0.284**
	(2.16)		(2.27)
$\%DII$		0.049	0.081
		(0.55)	(1.12)
Capital	-0.081	0.172**	-0.096
	(-0.94)	(2.09)	(-1.11)
$Log(Assets)$	-0.004	-0.065	-0.023
	(-0.16)	(-1.35)	(-1.08)
Year FE	Yes	Yes	Yes
Observations	53	53	53
R^2	0.458	0.207	0.488

Panel B: Tobit

	(1)	(2)	(3)
$\%FII$	0.356**		0.360**
	(2.23)		(2.25)
$\%DII$		-0.010	0.035
		(-0.11)	(0.43)
Capital	-0.215*	0.051	-0.223*
	(-1.86)	(0.79)	(-1.89)
$Log(Assets)$	0.012	-0.024	0.003
	(0.39)	(-0.58)	(0.09)
Year FE	Yes	Yes	Yes
Observations	73	73	73
Pseudo R^2	0.222	0.018	0.227

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.4. Shareholder Concentration

OLS Dependent variable is log(Actual NPL/Reported NPL). In the Tobit panel, the dependent variable is log of (Actual NPL - 0.15 x Incremental NPL)/Reported NPL. $\%Inst$, $\%FII$, and $\%DII$ are the percentage of bank equity shares held by institutional, foreign institutional, and domestic institutional investors. $\frac{1}{No.\ FII}$ is the inverse of the number of FII shareholders. $\frac{\%FII}{No.\ FII}$ is the average shareholding by FII. *Capital* is the Tier 1 Capital Ratio. All explanatory variables are measured in 2015 (prior to underreporting disclosures). Robust standard errors are clustered at the bank level.

Panel A: OLS

	(1)	(2)	(3)
$\%FII$	0.354**		0.385**
	(2.45)		(2.69)
$\frac{1}{No.\ FII}$	-0.004		-0.005
	(-0.40)		(-0.36)
$\%FII \times \frac{1}{No.\ FII}$	-0.320**		-0.408**
	(-2.31)		(-2.39)
$\%DII$		0.039	0.118
		(0.36)	(1.34)
$\frac{1}{No.\ DII}$		-0.060	0.110
		(-1.18)	(1.30)
$\%DII \times \frac{1}{No.\ DII}$		-0.019	-0.053
		(-0.45)	(-1.09)
Capital	-0.175	0.136*	-0.190
	(-1.39)	(1.89)	(-1.66)
$Log(Assets)$	-0.177*	-0.081	-0.192*
	(-2.03)	(-0.94)	(-2.01)
Year FE	Yes	Yes	Yes
Observations	52	52	52
R^2	0.560	0.240	0.603

Panel B: Tobit

	(1)	(2)	(3)
$\%FII$	0.477***		0.502***
	(2.81)		(2.81)
$\frac{1}{No.\ FII}$	0.025		0.005
	(1.26)		(0.21)
$\%FII \times \frac{1}{No.\ FII}$	-0.376**		-0.403**
	(-2.57)		(-2.19)
$\%DII$		-0.031	0.039
		(-0.30)	(0.45)
$\frac{1}{No.\ DII}$		-0.064	0.069
		(-0.68)	(0.67)
$\%DII \times \frac{1}{No.\ DII}$		0.013	0.009
		(0.32)	(0.15)
Capital	-0.351**	0.033	-0.339**
	(-2.31)	(0.35)	(-2.29)
$Log(Assets)$	-0.206**	-0.040	-0.187*
	(-2.06)	(-0.38)	(-1.77)
Year FE	Yes	Yes	Yes
Observations	72	72	72
Pseudo R^2	0.331	0.021	0.341

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.5. Role of the Board

OLS Dependent variable is log(Actual NPL/Reported NPL). *Board Size* is the number of board members. *RBI Mem* is an indicator equal to 1 if board member represents the RBI. All continuous explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Underreporting is observed in years 2016 and 2017. Panel A is estimated via OLS for the sample of banks we observe reporting divergences. Panel B contains results from a Tobit regression using the sample of all banks in 2016 and 2017. Observations are censored below by the 15% minimum GNPA required to report. Standard errors are clustered at the bank level.

Panel A: OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Board Size	-0.073	-0.042	-0.075	-0.070	-0.061	-0.059	-0.092
	(-1.12)	(-0.79)	(-1.14)	(-1.20)	(-1.04)	(-0.84)	(-1.27)
RBI Mem.		-0.283^{**}				-0.219^{**}	-0.096
		(-2.15)				(-2.05)	(-1.29)
CEO Chair			-0.098			-0.078	0.046
			(-1.09)			(-0.77)	(0.76)
%Outsiders				0.115		0.173	0.129
				(1.41)		(0.77)	(0.79)
%Audit Board Outsiders					0.103^{*}	-0.102	-0.134
					(1.74)	(-0.49)	(-0.78)
%FII							0.273^{**}
							(2.12)
Capital	0.162^{*}	0.068	0.140^{*}	0.096	0.088	0.046	-0.095
	(2.03)	(0.99)	(1.95)	(1.48)	(1.14)	(0.50)	(-1.07)
Log(Assets)	-0.037	0.006	-0.023	-0.019	-0.017	0.014	0.017
	(-1.29)	(0.17)	(-0.75)	(-0.65)	(-0.57)	(0.34)	(0.54)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52	52	52	52	52	52	52
R^2	0.218	0.302	0.234	0.282	0.258	0.352	0.533

Panel B: Tobit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Board Size	-0.067	-0.061	-0.061	-0.074	-0.065	-0.056	-0.086
	(-0.78)	(-0.92)	(-0.76)	(-0.86)	(-0.82)	(-0.78)	(-1.17)
RBI Mem.		-0.472^{*}				-0.375	-0.220
		(-1.85)				(-1.64)	(-1.51)
CEO Chair			-0.227			-0.107	0.060
			(-1.21)			(-0.67)	(0.46)
%Outsiders				0.117		-0.010	0.031
				(1.05)		(-0.04)	(0.18)
%Audit Board Outsiders					0.179	0.095	-0.039
					(1.65)	(0.39)	(-0.20)
%FII							0.336^{**}
							(2.02)
Capital	0.038	-0.095	0.004	-0.028	-0.080	-0.143	-0.261^{**}
	(0.60)	(-1.18)	(0.06)	(-0.37)	(-0.98)	(-1.63)	(-2.21)
Log(Assets)	-0.006	0.055	0.024	0.015	0.026	0.072	0.055
	(-0.19)	(1.14)	(0.55)	(0.37)	(0.71)	(1.18)	(1.21)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72	72	72	72	72	72	72
Pseudo R^2	0.023	0.112	0.050	0.044	0.063	0.129	0.268

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.6. FII instrumented by MSCI Index Inclusion

Table 3.6 estimates the effect of FII shareholding on NPL underreporting using an IV. The instrument, $MSCI$, is defined as 1 if the bank was included in the MSCI India domestic index in 2015 and 0 otherwise. The Columns (1) & (2) present the first stage where FII shareholding (standardized) is regressed on the instrument. Columns (3) & (4) present the reduced form regression. Columns (5) & (6) reports the second stage of the instrumented FII shareholding on NPL underreporting. All explanatory variables are measured in 2015 (prior to underreporting disclosures). All continuous explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Standard errors are clustered at the bank level.

Panel A: IV

	First Stage		Reduced Form		Second Stage	
	(1)	(2)	(3)	(4)	(5)	(6)
$MSCI$	1.278***	1.314***	0.502**	0.759**		
	(4.62)	(3.23)	(2.35)	(2.31)		
$\%FII$					0.393***	0.578***
					(2.84)	(3.26)
$Capital$	0.664***	0.685***	0.067*	0.074	-0.194*	-0.322**
	(6.43)	(4.05)	(1.76)	(1.19)	(-1.75)	(-2.05)
$Log(Assets)$	-0.194***	-0.071	-0.059**	0.022	0.018	0.063
	(-3.79)	(-0.26)	(-2.31)	(0.21)	(0.54)	(0.39)
$Liquidity$		0.162		0.045		-0.049
		(1.33)		(0.68)		(-0.73)
$MarketCap$		-0.340		-0.325*		-0.128
		(-1.06)		(-1.88)		(-0.55)
$FreeFloatMarketCap$		0.295		0.124		-0.046
		(0.92)		(1.35)		(-0.22)
$ForeignRoom$		0.158		0.064		-0.027
		(0.74)		(0.80)		(-0.23)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53	52	53	52	53	52
R^2	0.799	0.817	0.463	0.588	0.406	0.275
F First Stage	21.341	10.414				

Panel B: Tobit IV

	First Stage		Reduced Form		Second Stage	
	(1)	(2)	(3)	(4)	(5)	(6)
$MSCI$	1.144***	1.123***	0.586**	0.833**		
	(4.18)	(2.90)	(2.14)	(2.04)		
$\%FII$					0.490***	0.714***
					(2.72)	(3.14)
$Capital$	0.591***	0.607***	-0.013	-0.054	-0.308**	-0.483***
	(7.51)	(4.22)	(-0.25)	(-0.86)	(-2.30)	(-2.64)
$Log(Assets)$	-0.156**	-0.033	-0.065	0.209	0.019	0.227
	(-2.55)	(-0.10)	(-1.50)	(1.55)	(0.51)	(0.94)
$FreeFloatMarketCap$		0.325		0.178		-0.049
		(1.03)		(1.54)		(-0.21)
$Liquidity$		0.084		-0.131		-0.185**
		(0.68)		(-1.58)		(-2.30)
$MarketCap$		-0.338		-0.487**		-0.241
		(-0.97)		(-2.41)		(-0.84)
$ForeignRoom$		0.109		0.166		0.068
		(0.54)		(1.39)		(0.43)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73	72	73	72	73	72
R^2	0.740	0.753				
Pseudo R^2			0.194	0.307		
F First Stage	17.470	8.419				

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.7. Foreign Institutional Investors and Private Banks

OLS Dependent variable is log(Actual NPL/Reported NPL). In the Tobit panel, the dependent variable is log of (Actual NPL - 0.15 x Incremental NPL)/Reported NPL. $\%Inst$, $\%FII$, and $\%DII$ are the percentage of bank equity shares held by institutional, foreign institutional, and domestic institutional investors. $Private$ an indicator variable whether less than % 50 of the bank is owned by the state. $Capital$ is the percentage of Tier 1 Capital. All explanatory variables are measured in 2015 (prior to underreporting disclosures). All continuous explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Underreporting is observed in years 2016 and 2017. Panel A is estimated via OLS for the sample of banks we observe reporting divergences. Panel B contains results from a Tobit regression using the sample of all banks in 2016 and 2017. Observations are censored below by the 15% minimum GNPA required to report. Robust standard errors are clustered at the bank level.

Panel A: OLS

	(1)	(2)	(3)	(4)
$\%FII$	0.272**		0.295	0.034
	(2.16)		(1.52)	(0.48)
$Private$		0.569**	-0.079	-0.023
		(2.26)	(-0.24)	(-0.08)
$Private \times \%FII$				0.394**
				(2.12)
$Capital$	-0.081	-0.073	-0.068	-0.076
	(-0.94)	(-1.09)	(-0.78)	(-0.78)
$Log(Assets)$	-0.004	0.089*	-0.019	-0.042
	(-0.16)	(1.81)	(-0.29)	(-0.60)
Year FE	Yes	Yes	Yes	Yes
Observations	53	53	53	53
R^2	0.458	0.343	0.459	0.535

Panel B: Tobit

	(1)	(2)	(3)	(4)
$\%FII$	0.356**		0.310	-0.225
	(2.23)		(1.41)	(-1.44)
$Private$		0.816**	0.146	0.420
		(2.15)	(0.48)	(1.51)
$Private \times \%FII$				0.689**
				(2.46)
$Capital$	-0.215*	-0.226*	-0.231**	-0.250**
	(-1.86)	(-1.91)	(-2.13)	(-2.26)
$Log(Assets)$	0.012	0.151*	0.039	0.025
	(0.39)	(1.98)	(0.69)	(0.46)
Year FE	Yes	Yes	Yes	Yes
Observations	73	73	73	73
Pseudo R^2	0.222	0.166	0.225	0.328

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.8. Interaction of Remuneration and Monitoring

OLS Dependent variable is log(Actual NPL/Reported NPL). In the Tobit panel, the dependent variable is log of (Actual NPL - 0.15 x Incremental NPL)/Reported NPL. *Remun* is the log of total remuneration awarded to a bank's CEO in the year of underreporting. $\%FII$ is the percentage of bank equity shares owned by foreign institutional investors. All continuous explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Underreporting is observed in years 2016 and 2017. Columns (1) & (2) present OLS results conditional on a bank reporting divergences. Columns (3) & (4) present results from a Tobit regression using the sample of all banks in 2016 and 2017. Observations are censored below by the 15% minimum GNPA required to report. Standard errors are clustered at the bank level.

	OLS		Tobit	
	(1)	(2)	(3)	(4)
Remun.	0.263**		0.284*	
	(2.28)		(1.88)	
$\%FII$		0.068		0.170
		(0.89)		(1.50)
Remun. $\times$ $\%FII$		0.154**		0.196**
		(2.11)		(2.04)
Capital	0.008	-0.009	-0.123	-0.152
	(0.19)	(-0.15)	(-1.35)	(-1.56)
Log(Assets)	0.025	-0.045	0.047	-0.055
	(0.80)	(-1.46)	(0.95)	(-1.15)
Year FE	Yes	Yes	Yes	Yes
Observations	47	47	61	61
R^2	0.457	0.573		
Pseudo R^2			0.143	0.302

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.9. Historical Performance

Table 3.9 presents results from a panel regression estimated over 2005-2015. Dependent variables are 100 times GNPA scaled by Total Assets, 100 times Net Profit scaled by Total Assets, and Log(Advances). $\%FII$ is the percentage of bank equity shares owned by foreign institutional investors. $Capital$ is the Tier 1 Capital Ratio. Lev is total debt plus total deposits divided by total assets. $TobinQ$ is bank book value divided by market value of bank. All explanatory variables are contemporaneous with the dependent variables. All continuous explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Regressions include Bank FE and Year FE. All standard errors are clustered at the Bank level.

	GNPA	Net Profit	Advances
$\%FII$	-0.686***	0.178**	0.156**
	(-6.64)	(2.11)	(2.72)
$Capital$	-0.118	0.142	0.038
	(-0.93)	(1.59)	(0.84)
$Lev.$	-0.368***	-0.013	0.129*
	(-3.09)	(-0.13)	(1.92)
$TobinQ.$	-0.232	0.068	-0.044
	(-1.53)	(0.91)	(-0.77)
Year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	375	377	377
R^2	0.644	0.649	0.989

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 3.10. Compensation Regression by FII Groups

Table 3.10 presents results from a panel regression estimated over 2005-2015. Dependent variable is the log of total remuneration awarded to the Bank's CEO. The first column is estimated over the entire sample. The second and third columns are split by the median of the average of each banks' FII shareholding over the entire sample. ROE is the bank's return on equity in that fiscal year. $GNPARatio$ is Gross NPAs divided by advances. $\%FII$ is the percentage of bank equity shares owned by foreign institutional investors. All explanatory variables are contemporaneous with the dependent variables. All continuous explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Regressions include Bank FE and Year FE. Standard errors are clustered at the bank level.

	(1) Full Sample	(2) High FII	(3) Low FII	(4) Full Sample	(5) Full Sample
ROE	0.017	0.055	-0.188		0.084
	(0.26)	(0.85)	(-1.31)		(0.89)
$GNPARatio$	-0.262*	-0.270**	-0.055	-0.293**	
	(-1.93)	(-2.37)	(-0.15)	(-2.51)	
$Log(Assets)$	0.720**	0.797**	0.919	0.394	0.161
	(2.19)	(2.42)	(1.22)	(1.44)	(0.95)
$\%FII$				0.113*	0.220***
				(1.78)	(3.74)
$GNPARatio \times \%FII$				-0.194***	
				(-2.75)	
$ROE \times \%FII$					0.112***
					(3.04)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.86	0.91	0.40	0.86	0.86
Within R^2	0.06	0.13	0.01	0.09	0.07
Observations	274	153	121	274	276

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure 3.1. Timeline

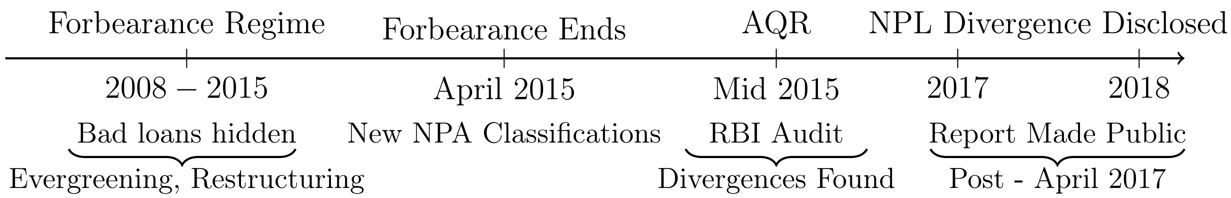
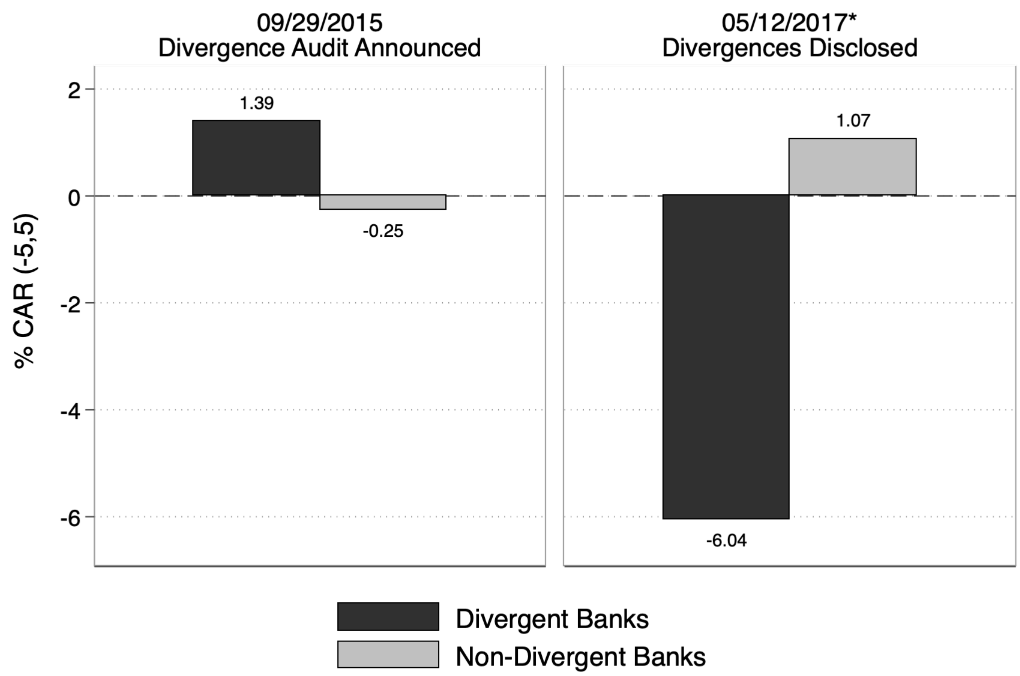


Figure 3.2. Event Study Reaction



*Divergence Disclosures are staggered with the first public disclosure on 05/12/2017

Figure 3.3. Economic Magnitude of Underreporting

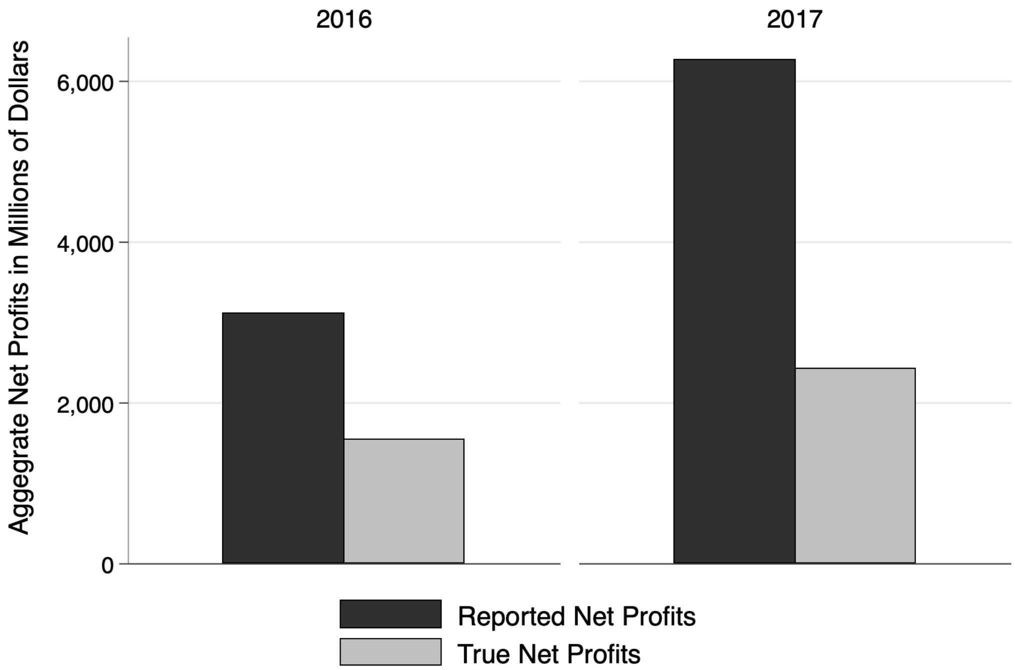


Figure 3.4. GNPA Underreporting by quantiles of %FII

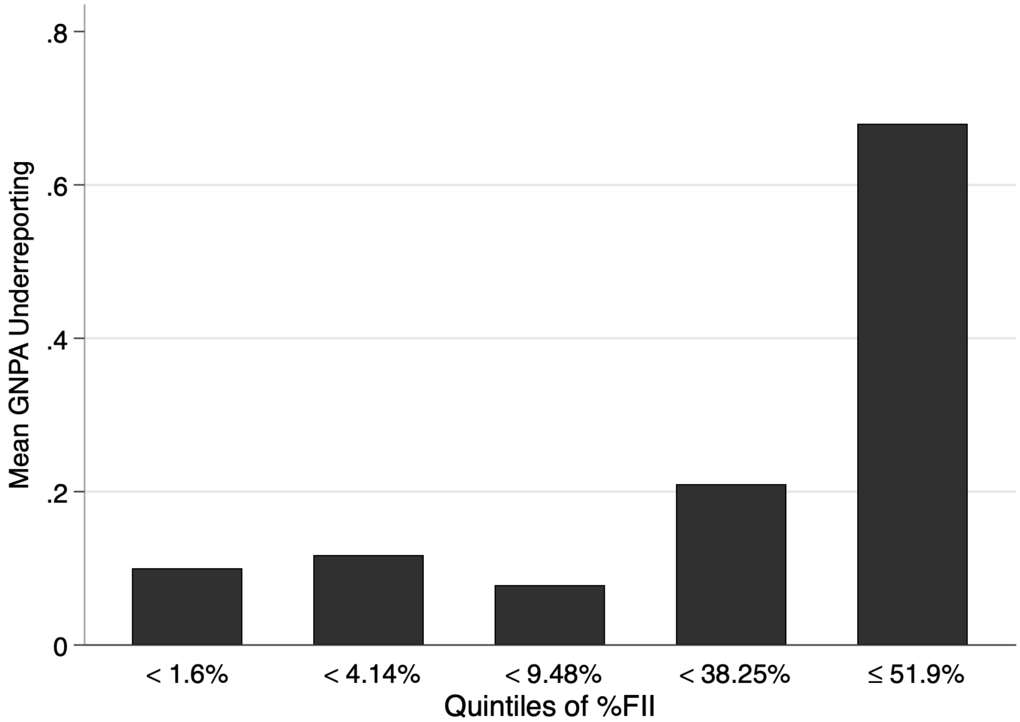


Figure 3.5. FII Shareholding by MSCI Inclusion Instrument

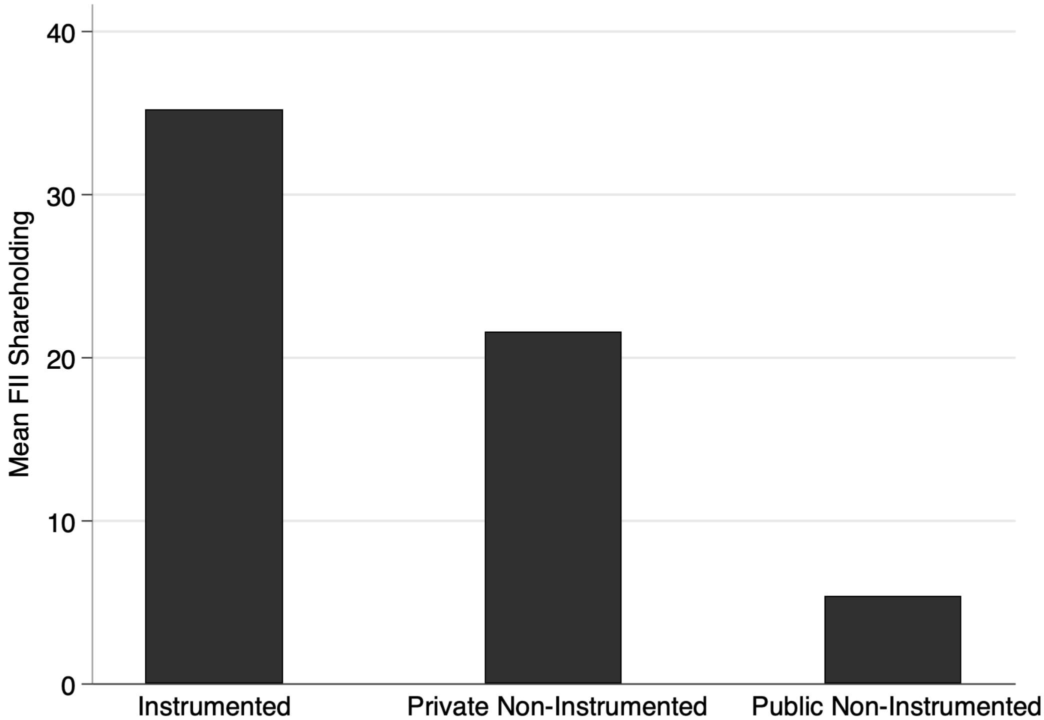


Figure 3.6. GNPA Underreporting by MSCI Inclusion Instrument

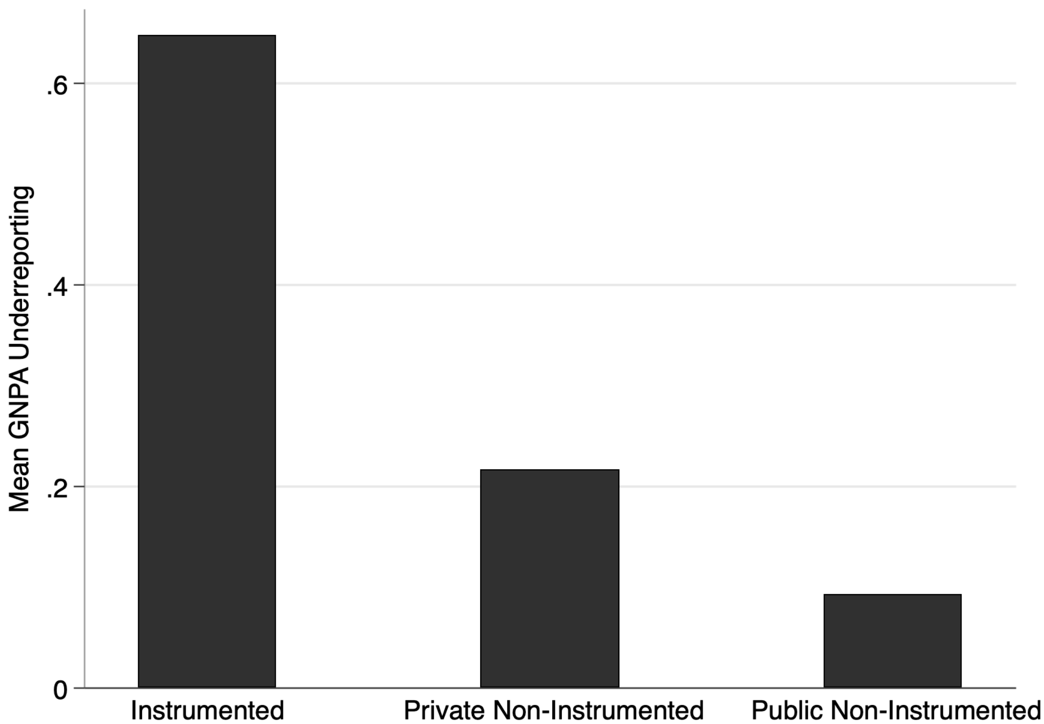


Figure 3.7. GNPA Underreporting by quantiles of Total Remuneration

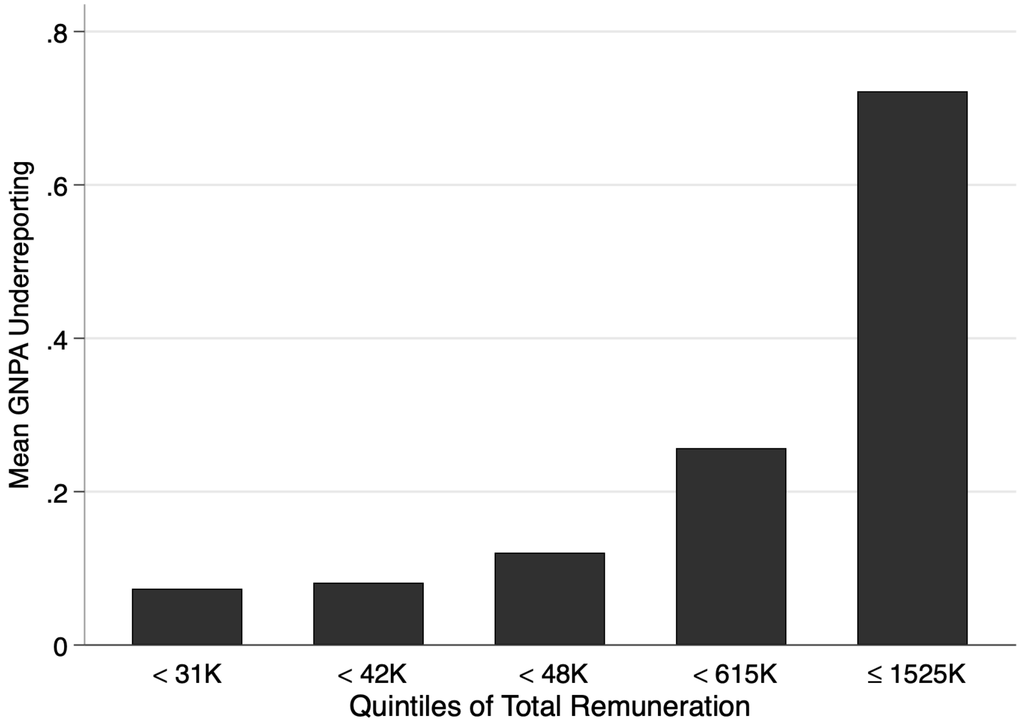
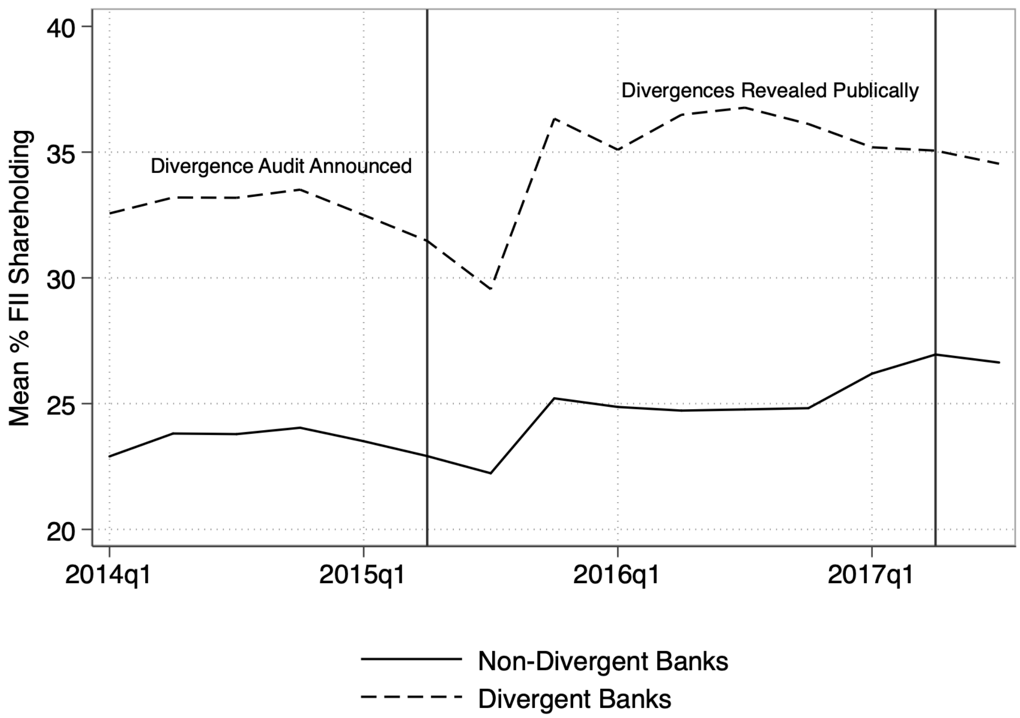


Figure 3.8. FII Holdings Timeline



A. Data Appendix to Chapter 1: The Value of Bank Lending

F. Proofs

F. Rollover Investment Strategy

Define the payoff to this strategy as:

$$\tilde{F}^{i,k}_{t+h} = z^i_{t+h-1} r^k_{t+h} - z^i_{t+h-1} - (z^i_{t+h} - z^i_{t+h-1}) = z^i_{t+h-1} r^k_{t+h} - z^i_{t+h}. \tag{3.3}$$

Let $z_t \in [0,1]$ for $t \leq H$. Assume the law of one price holds for every cash-flow horizon and $E_{t+h-1}[m_{t,t+h} r_{t+h}] = 1$ where m and r are one period SDF and returns, respectively. Define the pricing function $P_t(F_{t+h}) = E_t[M_{t,t+h} F_{t+h}]$. $M_{t,t+h}$ is the cumulatively compounded one-period SDF. This implies $P_t(F_{t+h}) = P_t(P_{t+1}(F_{t+h}))$.

Normalize t = 0. I will first prove $P_0(\sum_{j=1}^{H} \tilde{F}^{i,k}_j) = z_0 - P_0(z_H)$ by induction.

Set H = 1.

$P_0(\sum_{j=1}^{1} \tilde{F}^{i,k}_j) = P_0(\tilde{F}^{i,k}_1) = E_0[m_{0,1}(z^i_0 r^k_1 - z^i_1)] = z^i_0 - P_0(z^i_1)$

Next, assume that $P_0(\sum_{j=1}^{n+m} \tilde{F}^{i,k}_j) = z_0 - P_0[z_{n+m}]$.

It follows that

$$P_0(\sum_{j=1}^{n+m+1} \tilde{F}^{i,k}_j) - P_0(\sum_{j=1}^{n+m} \tilde{F}^{i,k}_j) = P_0(\tilde{F}^{i,k}_{n+m+1}) =$$
$$P_0(z^i_{n+m} r^k_{n+m+1} - z^i_{n+m+1}) = P_0(P_{n+m}(z^i_{n+m} r^k_{n+m+1} - z^i_{n+m+1})) =$$
$$P_0(z^i_{n+m} - z^i_{n+m+1})$$

Therefore $P_0(\sum_{j=1}^{n+m+1} \tilde{F}^{i,k}_j) = z_0 - P_0(z_{n+m+1})$. Thus, the premise is proved by induction.

Lastly, assume that for the first date $z_t = 1$ and $z_H = 0$ the final maturity date is known, after which the loan balance will be zero with certainty. (This is an innocuous assumption as

H can be set arbitrarily large while z_t for t less than H can take on any values).

With this additional assumption it immediately follows that

$$P_0(\sum_{j=1}^{H} \tilde{F}_j^{i,k}) = 1.$$

$\square$

F. Gain Investment Strategy

Define the payoff to the one-period gain strategy as:

$$\tilde{L}^{i,k}_{t+1} = r^k_{t+1} - (z^i_{t+1} - 1). \tag{3.4}$$

In subsequent periods, the payoffs accumulate recursively:

$$\tilde{L}^{i,k}_{t+h} = r^k_{t+h}\tilde{L}^{i,k}_{t+h-1} - (z^i_{t+h} - z^i_{t+h-1}). \tag{3.5}$$

The payoff to a gain strategy that goes long risky asset k and short a risk-free bond is:

$$G^{i,k}_{t+h} = \tilde{L}^{i,k}_{t+h} - \tilde{L}^{i,rf}_{t+h}. \tag{3.6}$$

I will prove $E_t[M_{t,t+h}G^{i,k}_{t+h}] = 0$ by induction. Normalize t = 0.

Set H = 1. $E_0[M_{0,1}G^{i,k}_1] = E_0[M_{0,1}(r^k_1 - r^{rf}_1)] = z^i_0 - z^i_0 = 0$

Next assume that $E_0[M_{0,n+m}G^{i,k}_{n+m}] = P_0(G^{i,k}_{n+m}) = 0$.

Note that $P_{n+m}(G^{i,k}_{n+m+1}) = P_{n+m}(r^k_{n+m+1}\tilde{L}^{i,k}_{n+m} - r^{rf}_{n+m+1}\tilde{L}^{i,rf}_{n+m}) = \tilde{L}^{i,k}_{n+m} - \tilde{L}^{i,rf}_{n+m} = G^{i,k}_{n+m}$.

It follows that $P_0(G^{i,k}_{n+m+1}) = P_0(P_{n+m}(G^{i,k}_{n+m+1})) = P_0(G^{i,k}_{n+m}) = 0$.

□

F. Data Construction

Loan Cash-Flow Construction

F. Sample Formation

I apply the following sample filters:

1. I limit the sample to term loans.

2. I keep floating LIBOR loans only.

3. I limit the sample to loans with less than or equal to 8 years original maturity.

4. I drop financial firms and public industry (sic codes starting in 9) from the sample.
5. I require that the match file has a 100% ticker match or at least a 50% company name match score in the Chava and Roberts (2008) Compustat linking file.
6. I require that the firm is active in Compustat at the time of loan origination.
7. I drop loans whose purpose is exit financing or debtor in possession financing.
8. I require that the loan amount is at least 1 million.
9. I drop LBOs because there is limited or no repayment data for these firms.
10. I drop firms that are refinanced within one quarter of origination.

F. Scheduled Cash-Flows

I take the following steps to construct a series of scheduled loan cash-flows:

1. I use the amortization schedule, upfront fees, and interest rates from Dealscan to construct a series of scheduled quarterly cash-flow payments. I get quarterly Libor 3M rates from FRED. I use the spread over LIBOR from the Dealscan pricing file. Because the sample consists entirely of floating-rate loans, the interest rate in any period is the LIBOR base rate plus the spread. I assume that all the loans apply quarterly interest because I construct a series of quarterly cash-flows.
2. I merge the performance pricing file to Compustat to allow the interest rate spread to vary over time if the firms' financial and net worth ratios change according to the performance pricing schedules.
3. I use the amortization schedule from the facility payment schedule Dealscan file. In addition to the payment schedule file, I analyze the Dealscan loan comment, which sometimes indicates whether a loan amortizes "5% per year." If a loan's amortization schedule is not available, I impute the amortization schedule by taking the average

amortization rate for a given loan type (Term Loan/Term Loan A/ Term Loan B) in a given year. I assume the loan amortizes linearly at this rate. In general, a Term Loan A amortizes quickly, while a Term Loan B is more similar to a bond and may not amortize until a final payment. Table A.3 shows the baseline results are robust if I assume that Term Loan A amortizes 100% before maturity and Term Loan B does not amortize at all.

4. Berg et al. (2016) shows Dealscan is missing the upfront fees on many loans. Therefore, I impute the loan fees rather than ignoring missing observations. For loans without information on upfront fees, I impute the fess by regressing the fee on a year dummy, the log of the loan amount, the loan amount, the loan amount squared, the interest rate spread, the log of the interest rate spread, a loan purpose dummy, a loan type dummy, whether the loan has a prepayment penalty, and whether the loan is secured. I take the predicted value as the imputed loan fee. Table A.3 shows the baseline results are robust if do not impute upfront fees and assume they are zero if missing.

F. Identifying Loan Prepayments

I obtain prepayments/refinancing dates from several sources.

1. I take prepayment information straight from the Dealscan amendment file. I identify refinancing from the amendment file for entries which, indicate the loan was "refinanced," "prepaid," "repaid," "rolled over," "cancelled," or "terminated". For these entries, I take the refinancing date as the amendment date from this file.

2. I apply a loan matching algorithm to identify refinancing not explicitly covered by the Dealscan amendment file. This algorithm exploits that most loans in Dealscan are refinancing of previous loans (Roberts and Sufi, 2009). For each loan, I merge all future loans/notes issued by the same borrower before the original loan's maturity date. I limit these matches to a set of loans that have a "refinancing" indicator in Dealscan, the loan purpose is debt repayment or the comment that indicates that the loan refinances

a previous loan/amends and restates a previous loan. Often there are more than one loan matches that meet this criterion. To determine the correct loan refinancing pair, I rank the matches based on the similarity of the loan pairs. The idea behind this ranking is that loans with similar characteristics are more likely to be a refinancing match. I rank potential refinancing using the following characteristics: Same Security, Same Loan Purpose, Same Loan Type, Same Loan Amount, Loan Amounts are 20% similar, Same Loan Amount, Similar Loan Maturity, Lower Loan Spread, Higher Loan Spread, Same Lead Lender, Years Until Loan Is Refinanced, Loan Does Not Have a Refinancing Indicator, Loan Refinanced After a Merger. I define an exact loan match as a pair that has the same loan purpose and similar loan maturities. For loans without an exact match, I manually calibrate the relative weights/importance of these characteristics by comparing the matched pairs to actual refinancing information from SEC filings. For example, this algorithm identifies that Commercial Intertech Corp's 60 million Oct 1996 term loan was paid off by the issuance of 60M notes in July 1997. I manually verify this with SEC filings: "Net proceeds were used to repay $60.0 million outstanding under the Company's term loan facility which was negotiated at the end of fiscal 1996."

3. I identify loan prepayments using textual analysis of 10-K and 8-K SEC Filings. Because the sample consists entirely of firms in Compustat, I can access SEC filings for the entire sample. For each firms' filings, I look for hits that at least one of each of following lists of phrases within 20 words of each other in the same sentence: ('to refinance,' 'refinanced,' 'terminated,' 'repay,' 'repaid,' 'pay off,' 'prepaid,' 'pre-paid,' 'principal pre-payments,' 'retire,' 'retired,' 'reduce borrowings') AND ('term loan,''Term Loan,''Term loan,' 'Credit Agreement,' 'credit agreement,' 'Credit agreement,' 'Credit Facility,' 'Credit facility,' 'credit facility,' 'loan'). I merge these potential hits to all of the borrowers outstanding loans. Of the matches, I then manually read each of the hits to verify that the textual algorithm identified that loan's refinancing. An example of a successful hit from a 10-K using this criterion is Consumers Energy Co "used the net proceeds to pay off a $150 million term." I use the filing date of the earliest hit as the

refinancing date. I use the web-scraped data for loans that have not been refinanced by the amendment file or loan matching algorithm by four years following maturity. The web-scraping approach is able to capture loans that are paid down without refinancing and therefore capture loan prepayments not picked up by the loan matching algorithm.

4. I web-scrape 8-Ks for announcements of mergers and assume that loans are refinanced if they are outstanding at the time they are acquired by another company. This assumption is driven by the anecdotal observation that firm loans are often refinanced, and debt is consolidated upon merging.

5. I take loan amendment dates from Loan Connector and use these as refinancing if none of the above criteria has been satisfied.

6. If a loan is prepaid, I use the prepayment penalty data from Loan Connector to apply a prepayment penalty, if applicable, to the loan cash-flows.

7. The amendment file includes changes to the loan maturity, interest rate, or amount changes I treat these observations as *de facto* loan refinancing. I assume the loan balance is repaid at the time of the refinancing, and I create a new loan observation with the new modified loan contract term at the date of the modification.

8. I take a random sample of 100 loans and read SEC 10-Ks, 8-Ks, and 10-Qs to confirm whether a loan was refinancing on the date which the result of the algorithm determined. I find that the procedure is 94% accurate at determining the correct date of the loan refinancing.

[See Figure A.1]

F. Identifying Loan Defaults and Recoveries

I take the following steps to construct the loan default and recovery information:

1. I begin with collecting all bankruptcies from the UCLA bankruptcy database. This database covers firms with more than $100M in assets, which accounts for nearly the entire loan sample. To capture bankruptcy information for firms not covered by the UCLA database, I augment this dataset with information from Dealscan and determine that a firm bankrupts if it later receives exit financing or DIP financing. I web-scrap 8-k filings to obtain bankruptcy filing status. Finally, I manually search for bankruptcies for firms with less than $100M in assets in the sample. I match the bankruptcies to firms in Compustat. This procedure results in a comprehensive database of bankruptcies for firms in my sample.

2. I assume a loan defaults if it is outstanding 90 days prior to when a firm files for bankruptcy. I take industry and yearly loan loss-given-default from Moody's Annual Default Report. I start with the yearly average loan loss given default. For each Moody's industry, I add the difference between the average industry recovery and the overall average to the yearly loss given default. If a loan is unsecured or second-lien, I subtract the difference between the average loan loss given default and the average unsecured loss given default (the difference is roughly 30%). This procedure results in a series of industry-by-year by security loan recovery rates. Starting in 2005, Moodys Annual Default Report started to report loan level recoveries. Table A.3 shows how the baseline results change using loan-level recoveries when available. I assume the loan recovery is applied immediately because Moody recovery rates are computed as discounted values at the of default.

Corporate Bond Return Details

I apply the following sample filters and steps to construct a sample of corporate bond returns:

1. I start with a sample of corporate bonds in Mergent FISD and apply the sample filters in Bai et al. (2019).

2. I additionally impose that bonds have a valid rating from Moody's or S&P with at least a CCC rating.

3. I only keep bonds issued by non-financial firms (Industry Group =1).

4. I keep only keep semi-annual coupon bonds with $1000 face value.

5. I keep bonds with 20 years remaining maturity or less.

6. For July 2002 and onward, I take returns from WRDS bond returns.

7. Prior to July 2002, I follow Bai et al. (2019) and construct bond returns using coupon information from FISD and transaction prices in NAIC (1994–2002) and prices Datastream (1992–1994).

8. This gives me bond-level return data from 1992 onward.

Using bond-level returns, I construct returns to corporate bond portfolios. I form portfolios by sorting by bond characteristics.

- <u>Corporate Bond Market Portfolio Return</u> Value-weighted portfolio consisting of all corporate bonds in the sample.

- <u>Credit Risk Factor (CRF) Portfolio Returns</u> Value-weighted portfolios consisting of corporate bonds with the lowest quintile credit rating (Bai et al., 2019).

- <u>Downside (DRF) Bond Portfolio Returns</u> Value-weighted portfolios consisting of corporate bonds with the lowest quintile VAR in the past 36 months (Bai et al., 2019).

- <u>Callable Bond Portfolio Returns</u> Value-weighted portfolio consisting of callable corporate bonds in the sample.

Bond Yield and Loan Announcement Details

Loan-Bond Spreads

- I gather all senior bonds issued by the company 120 days prior to the start of the loan facility.
- Following Agarwal et al. (2021), within these matched bonds, I select the bond with the closest maturity to the loan facility.
- I additionally require that the bond have no more than 16 years of maturity and have a fixed or zero coupon.
- I subtract from the bond yield, yield from a treasury security with identical maturity.

Loan Announcement Returns

- For each firm in the sample, I identify news articles in ProQuest related to loan announcements.
- Of the potential matches, I manually read articles to confirm that the new article indicates the firm has acquired a new loan, and it is the first news related to this event.
- I match these events to the loans in the sample.
- I compute cumulative abnormal stock returns in a (-3,3) event window using the market model from WRDS event study.
- Similarly, I use corporate bond transaction data from TRACE to compute the difference in bond yields implied by the transaction prices in (-3,3) event window.

Investment Strategy Examples

[See Table A.1]

[See Table A.2]

[See Figure A.2]

Loan Characteristics

I obtain and construct loan characteristics variables in the following way:

1. I take borrower characteristics including total assets, age, and whether the firm has a credit rating from Compustat. I follow (Hadlock and Pierce, 2010) and truncate firm age at 37 years. I merge Compustat to FISD using firm CUSIPs and the WRDS corporate bond mapping file to determine whether the company has ever issued a corporate bond.

2. I obtain lender characteristics including book equity, market equity, bank size, and bank operating expenses from Compustat. I define lead lenders using the 'LeadArrangerCredit' variable in Dealscan. If there are multiple lead lenders, I take the average of the lender characteristics.

3. I define the lending relationship variables using the lead banks within Dealscan. I use the borrower's city in Dealscan and the Lender's Compustat Headquarters city to define physical distance in miles.

4. I take whether the loan is collateralized and its maturity from Dealscan. I do not include observations where 'secured' variable is missing in Dealscan.

5. I take the loan lead retention amount from Dealscan and impute missing observations following the Chodorow-Reich (2014) imputation methodology.

F. Additional Robustness Tests

F. Sensitivity Analysis

[See Table A.3]

F. Expense Ratio Sensitivity Analysis

[See Table A.4]

F. Alternative Risk-Adjustment Procedures

Using the new dataset of loan cash-flows, I compute the risk-adjusted returns of loan cash-flows using the methodologies in Ang et al. (2018) and Cochrane (2005). I find that the average risk-adjusted returns are positive and higher than the estimates in this paper. Using the Ang et al. (2018) procedure, I find a risk-adjusted return of 3.3%. Using the Cochrane (2005) methodology, I find a risk-adjusted return of 2.8%.

F. Factor Robustness

I perform the Gagliardini et al. (2019) test on loan cash-flows to check whether the loan benchmarks constitute the approximate factor structure. Alternatively, there is an omitted common factor the loan benchmarks cannot explain. To perform this test, I form 30 buckets of loan portfolios and estimate the baseline model on each of them. Then I compute the residuals of the estimates and take the largest eigenvalue to check for whether there is a significant enough unexplained common factor. Gagliardini et al. (2019) develops a formula to determine whether the eigenvalue passes a critical threshold to constitute an omitted factor. Unlike a standard asset pricing factor model, this model has several cash-flow horizons for each origination quarter. Therefore, I compute the Gagliardini et al. (2019) criteria separately for each cash-flow horizon.[23] Figure A.3 shows the results of this exercise. I find that all cash-flows horizons pass the test. I conclude that the loan benchmark funds constitute an approximate factor structure for loan cash-flows.

[See Figure A.3]

[23]Because I estimate the model pooled over all cash-flow horizons and origination quarters, I cannot compute the trimming function they use in the paper to mitigate multicollinearity in the factors. The paper shows the trimming function is not needed, however, for the test statistic to asymptotically obtain. I document that multicollinearity is not a problem in the elastic net robustness section of the paper.

F. Transaction Costs

The current analysis in the paper assumes that an investor can purchase stocks and bonds at no cost. If the replicating portfolio estimated in this paper required transaction costs, this would imply a risk-adjusted return larger than the 190 bps reported. Frazzini et al. (2012) estimate that corporate bonds and stocks have transaction costs of 20bps and 10bps, respectively. A significant fraction of the replicating portfolio, however, invests in treasury bonds for which transaction costs are near zero. Conservatively assuming that the entire replicating portfolio required a transaction cost of 20 bps on a $1 investment, annualized over a duration of 1.7 years, would imply a larger risk-adjusted return of 202 bps. The effect of transaction costs on risk-adjusted returns, therefore, is unlikely large enough to bias the cross-sectional results.

F. Shadow Cost of Bank Capital

The baseline risk-adjusted returns are calculated using the principle that the appropriate discount rate for a stream of cash-flows depends on the riskiness of those cash-flows. Financial frictions making it more costly for banks to use equity may affect the appropriate discount rate to finance these investments. Likewise, a bank using more insured deposits can lower the required rate to finance loans. The baseline analysis does not consider how these frictions in banks' capital structure affect the risk-adjusted income they earn. However, I provide a conservative bound on how these costs could affect the risk-adjusted return estimates. Using the estimates from Kashyap et al. (2010), a rough calculation shows that to finance a loan with an extra 6% Tier 1 equity with 50% of the loan maintained on the balance sheet requires an additional shadow cost of 14 basis points. This additional shadow cost is inadequate to explain the 190 basis points of risk-adjusted return or the differences in the magnitude of the cross-sectional results.

F. Additional Results and Figures

[See Figure A.4]

F. Time Series Variation

The main results in the paper focus on the unconditional risk-adjusted performance pooled across the entire sample period. This aids identification by analyzing how the loan cash-flows covary with security market payoffs over a time period that contains three business cycles using over 20 years of returns. Reporting the unconditional average also makes a weaker assumption that the SDF is unconditionally orthogonal to the residuals. If I make the stronger assumption that the SDF is orthogonal to the residuals at every point in time, then I can say something about the time series of the value added. I can help relax this assumption by estimating the risk loadings separately over different time periods. In particular, I re-estimate the baseline model separately on the pre- and post- great financial crisis periods. I report the estimated value add using this procedure below in Figure A.5.

[See Figure A.5]

F. Promised Yield and Credit Spreads

To estimate the implied credit spread from the asset pricing model, I re-estimate the baseline specification while falsely assuming that loan loss-given defaults are 0%. Doing so effectively discounts the promised loan cash-flows at the risk-free rate. I calculate the implied credit spread by taking the difference between the annualized promised return and the risk-adjusted return computed in the baseline specification. I report results for both value-weighted and equal-weighted portfolios below.

[See Table A.5]

[See Figure A.6]

[See Figure A.7]

[See Figure A.8]

I estimate whether there is any systematic difference in value added for terms loans with and without revolvers in the package. I find no statistically significant difference in value added between these two sets of loans.

[See Table A.6]

I repeat the analysis from Table 1.3 on the sample of loans prior to the great financial crisis, during which there is no difference in bank capital risk-weights across syndicated loans. I find similar results to Table 1.3.

[See Table A.7]

I estimate whether firms with issued corporate bonds have different value added. I find that borrowers with corporate bonds have a statistically significant lower value added than those without bonds.

[See Table A.8]

[See Table A.9]

As an alternative measure of screening and monitoring intensity, I use the loan spread. In the economic framework in Appendix E, a loan spread consists of two parts: compensation for systematic risk and the value added by bank lending services for mitigating financial constraints. Two sources of variation, therefore, can drive higher loan spreads: credit risk and higher value added by banks. By construction, the risk-adjustment methodology differences out the first component, leaving the value added by the bank. Holding credit risk fixed, banks charge higher interest rates if they are involved in mitigating more severe financial constraints and earn more risk-adjusted income as a result. Consistent with this framework, I show that loans with higher spreads have higher risk-adjusted returns.

[See Table A.10]

I measure risk-adjusted returns sorted on portfolios of loans based on the tightness of their loan covenants. As a measure of loan covenants, I use the Murfin (2012) measure of loan covenants for earning-based covenants following Kermani and Ma (2020). Consistent with banks monitoring more intensely when they set tighter covenants, I find that banks earn higher risk-adjusted returns when they set tighter covenants.

[See Table A.11]

F. Economic Framework

I begin by describing an economic framework for analyzing the value of bank lending using the bond market as an example of a firm's outside financing option. Borrowers' cost of capital broadly consists of three components: the risk-free rate, r_f; the risk premium in a frictionless market, r_{risk}; and the risk premium from financing frictions specific to the market from which the firm borrows. Let the financing frictions specific to the bond market be denoted by θ_{bond}. The cost of capital of a firm using the bond market is:

$$r_{firm,bond} = r_f + r_{risk} + \theta_{bond}. \tag{3.7}$$

Consider a bank loan as an alternative financing choice.[24] Bank loans are special because banks' information production and monitoring abilities can mitigate financing frictions better than a public capital market, resulting in a lower required return for bank lenders to finance the project, $\theta_{loan} \leq \theta_{bond}$ (Holmstrom and Tirole, 1997).[25] Mitigating these frictions, however, requires that banks pay γ to compensate loan officers and cover other expenses.[26] In equilibrium, banks must capture a portion of the total value created, ψ, to cover these expenses of screening and monitoring. This inequality corresponds to the intermediary's incentive compatibility constraint in Holmstrom and Tirole (1997).

$$\psi - \gamma \geq 0 \tag{3.8}$$

[24]In this setup, I exclude the possibility that obtaining a loan spills over and mitigates frictions in the bond market (Weston and Yimfor, 2018). Although this framework is cast in terms of a binary choice between a bond and a loan, it is easy to think how it extends to a weighted average cost of capital setting, whereby the firm will take a loan if and only if it lowers its overall cost of capital. The borrower may benefit indirectly across markets if the information production of lending spills over, lowering bond yields and raising stock prices as in James (1987) and Weston and Yimfor (2018). By revealed preference, the borrower will still take the loan when doing so reduces its weighted average cost of capital.

[25]In general, a bank's screening and monitoring can either raise the expected cash-flows the bank will collect or lower the discount rate on those cash-flows. Because this framework presents the cost of capital as a discount rate on a promised stream of cash-flows, both effects are captured by this discount rate.

[26]It is useful to empirically think of these costs as an increasing function of the intensity of the bank's screening and monitoring: $\gamma(.) = \gamma(\theta_{bond} - \theta_{loan})$. As such, even in a competitive equilibrium, the value added to the bank is informative about the total surplus created: $(\theta_{bond} - \theta_{loan})$.

In a competitive equilibrium, banks will earn just enough of the total value to pay loan officers and other expenses $\psi = \gamma$.[27] A borrower will choose a bank loan if and only if the borrower's value is positive, capturing the remaining value via a lower cost of capital:

$$((\theta_{bond} - \theta_{loan}) - \psi) = (\theta_{bond} - (\theta_{loan} + \psi)) \geq 0. \tag{3.9}$$

The resulting cost of the capital on a loan will consist of the new risk premium required in the lending market, $r_{risk} + \theta_{loan}$, plus a risk-adjusted term, ψ, that measures the value-added to the bank:

$$r_{firm,loan} = r_f + r_{risk} + \theta_{loan} + \psi. \tag{3.10}$$

If the loan market is less than perfectly competitive, the bank shareholders will earn rents $\psi \geq \gamma$. However, the borrower's value must still be strictly greater than zero; otherwise, it will not take the loan.[28] The total social value can be decomposed into the lender's value added on the loan and the borrower's value:

$$\underbrace{(\theta_{bond} - \theta_{loan})}_{\text{Total Value}} = \underbrace{\psi}_{\text{Lender Value Added}} + \underbrace{(\theta_{bond} - (\theta_{loan} + \psi))}_{\text{Borrower Value}}. \tag{3.11}$$

This equation indicates that, by revealed preference, the lender's value added is a lower bound on the total social value. Empirically, the value added by the bank corresponds directly to the risk-adjusted income on a bank loan, the object of study in this paper. The borrower's value corresponds to the difference between a firm's cost of capital in the bond and loan market. Importantly, the borrower's value reflects that firms face different financial frictions in the bond and loan markets, $(\theta_{bond} - \theta_{loan})$, whereby banks may have an advantage in mitigating these frictions.[29]

[27] Although γ represents the compensation to loan officers, this framework does not take a stance on the surplus that the labor of the bank may enjoy, which may arise from the scarcity of skilled human capital.

[28] If managers' incentives are misaligned, it is also possible the bank destroys value for shareholders and $\psi < \gamma$.

[29] For instance, a borrower going to the bond market may face adverse selection, moral hazard, renegotiation frictions, and bankruptcy costs, which banks can help attenuate.

F. Figures and Tables

Figure A.1. Loan Refinancing Examples

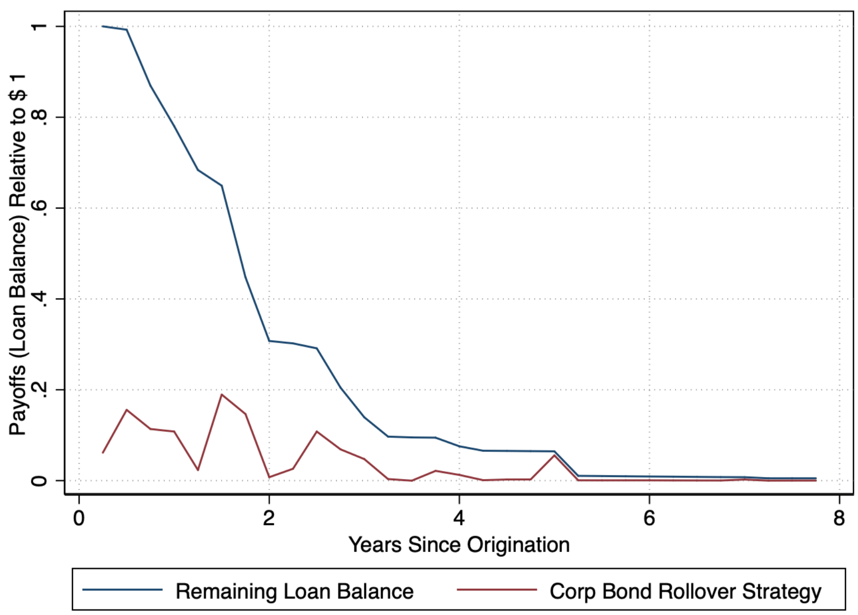
Figure A.1 lists examples of refinanced loans, including their original maturity, refinanced date, and text extract confirming the refinancing.

Company Name	FacilityStartDate	FacilityEndDate	FacilityAmt	Refinance Date	Refinance/Amendment Comment	Note
Pantry Inc	19990128	20060131	160000000	19991130	"Credit replaces an existing deal dated 01/28/99 for $210M."	Comment is from Dealscan
Charles River Laboratories International Inc	19990929	20070929	120000000	20030301	"During 2002 we terminated our revolving credit facility and repaid all of our variable-rate term loans."	Repayment of term loan in 2002 reported in 2003Q1 10-K
Alpha Technologies Group	20001226	20051226	35000000	20020301	"The Company used $3,661 000 to repay the credit facility entered into on April 16,1999"	December 26, 2000 Term Loan refinanced April 16, 1999 Term Loan referred to in SEC filing
Accuride Corp	20030613	20070613	180000000	20031210	"We are very pleased to have completed the refinancing of our senior credit facilities in June (the "Refinancing") and subsequent re-pricing in December 2003."	New Loan in Dealscan with new pricing replaces June 2003 observation.
LEXINGTON PRECISION CORP	20031218	20060630	11500000	20060531	"with the refinancing of substantially all of our secured debt we received proceeds of $27,500 000 from a new equipment term loan and a new real estate term loan and repaid revolving loans of $6,923 000 secured term loans"	
Talx Corp	20040331	20090331	10000000	20050414	"On April 14, 2005, we entered into a $100.0 million secured second amended and restated loan agreement (the "2005 Loan Agreement") with LaSalle Bank National Association, as administrative agent and the lenders party thereto (collectively, the "Lenders"), to replace the 2004 Loan Agreement and refinance in full the $57.5 million outstanding loan balance"	
URS Corp	20050127	20080822	270000000	20071115	"Upon entering into the 2007 Credit Facility we terminated and repaid the remaining $39.0 million outstanding balance on our 2005 senior credit facility (2005 Credit Facility)."	
INVERNESS MEDICAL INNOVATIONS INC	20050630	20080331	20000000	20070626	"We terminated our June 2005 senior credit facility in conjunction with our refinancing activities discussed above."	
CUMULUS MEDIA INC	20050714	20120714	400000000	20060607	"The proceeds were used by the Company to repay all amounts outstanding under its 2005 credit facility"	
SUPERVALU INC	20060601	20110602	750000000	20070308	"On March 8, 2007, the Company executed an amendment to the existing credit facility, resulting in new applicable interest rates for Term Loan A and Term Loan B."	
FREEPORT MCMORAN COPPER GOLD INC	20070319	20140319	7500000000	20070710	"Amendment Agreement dated as of July 3, 2007, amending the Senior Secured Credit Agreement dated as of March 19, 2007"	New loan with features of amendment replaces this observation in Dealscan
XOMA LTD DE	20080509	20130509	55000000	20100301	"In September of 2009, we fully repaid our term loan facility with Goldman Sachs, which was a five-year term loan facility originally entered into in November of 2006 and refinanced in May of 2008."	Repayment of term loan in 2009 reported in 10-K reported in 2010Q1.
Gogo Inc	20120621	20170621	135000000	20130404	"On April 4, 2013, we borrowed $113.0 million (the "New Borrowing") under an amendment to the Credit Agreement governing the Senior Term Facility. We refer to our existing Senior Term Facility, as so amended, as the "Amended Senior Term Facility." The amendment increased the size of the Senior Term Facility from $135.0 million to $248.0 million."	New loan with features of amendment replaces this observation in Dealscan
Service Corp International	20130702	20180702	600000000	20160303	"We used $550.0 million of the Term Loan due March 2021 and $30.0 million of the Bank Credit Facility due March 2021 to repay $270.0 million outstanding borrowings on the Bank Credit Facility due July 2018 and $310.0 million outstanding borrowings on the Term Loan due July 2018. "	This extinguished the entire remaining balance

Figure A.2. Loan Benchmark Examples

This figure plots examples of the rollover and gain benchmark funds investing in the corporate bond market portfolio.

((a)) **Panel A:** Rollover Loan Benchmark



((b)) **Panel B:** Gain Loan Benchmark

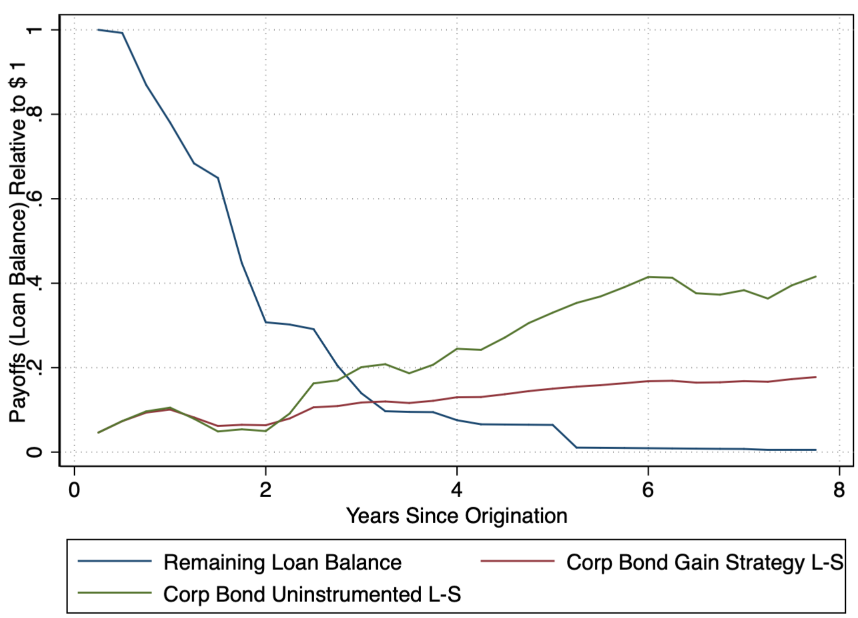


Figure A.3. Diagnostic Criteria

Figure A.3 plots the max eigenvalue and penalty function from Gagliardini et al. (2019) for each cash-flow quarter horizon.

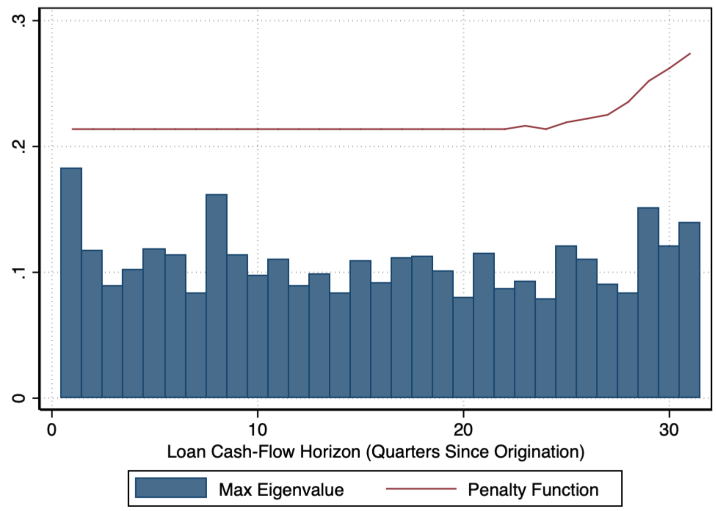


Figure A.4. Value Creation at Different Stages of Intermediation

This figure demonstrates the different stages of value creation in financial intermediation. The value added from lending can flow to many different stakeholders at different stages of the intermediation chain since they hold different types of contingent claims on the banks. For instance, the value added from bank lending could flow to the bank shareholders or debtholders. Managers at the bank may also capture some of the value from lending through compensation contracts. Taxpayers also have a contingent claim on the bank through government guarantees that may occur through the government injecting a subsidy through a bailout. Existing literature also studies whether borrowers obtain value from bank loans relative to alternative financing options. The measure of value added by bank lending in this paper looks directly at the value of the cash-flows the borrower pays to the bank, without taking a stance on how this value is distributed among these stakeholders.

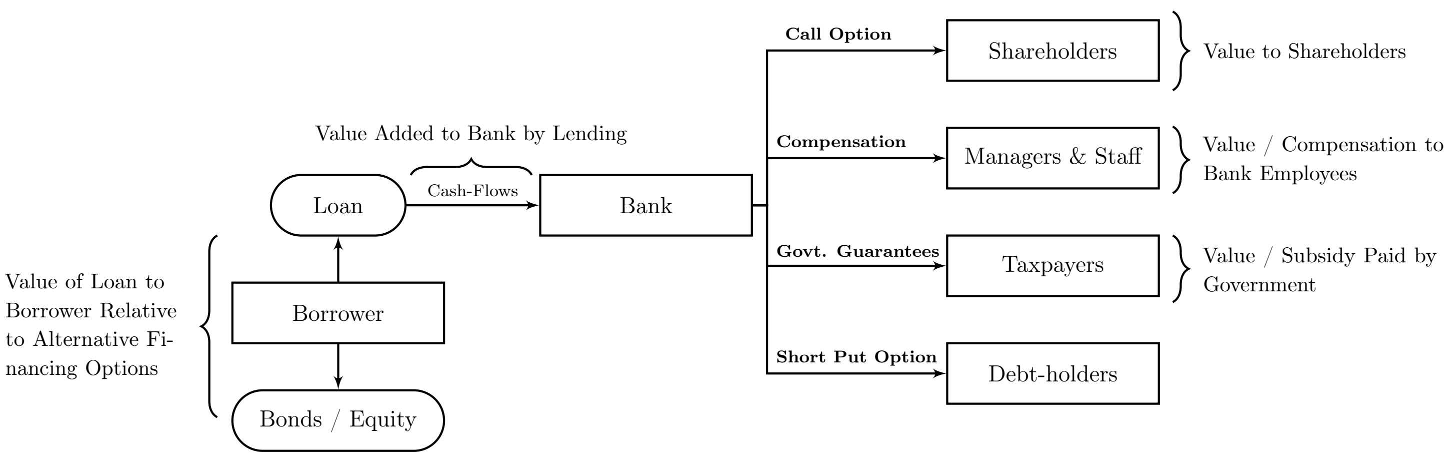


Figure A.5. Unit Value Added Over Time

Figure A.5 plots the average unit value added over time. Unit value added, ψ, is the annualized risk-adjusted returns and computed using the third column specification in Table 1.2. Risk loadings are estimated separately for pre- and post-great financial crisis periods.

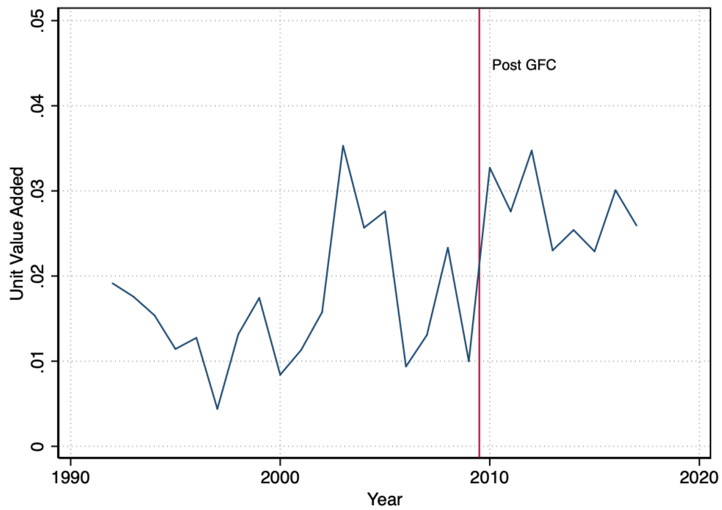


Figure A.6. Sample Loan Interest Rates

Figure A.6 plots the average loan interest rate over time weighted by the fraction of the outstanding loan balance.

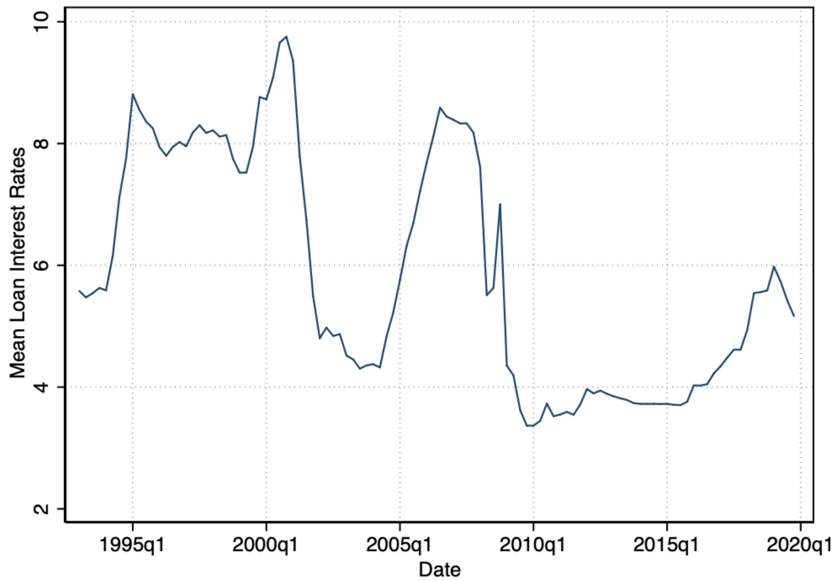


Figure A.7. Loan Sample Default Rates

Figure A.7 plots the volume-weighted average default rate for the loan sample. Default is an indicator for whether the loan defaults at any point while it is outstanding. The average default rate is computed by taking the fraction of outstanding loans that default at any point while they are outstanding and dividing by the total volume of loans outstanding. Although the security returns data extend until 2021Q2, nearly all of the sample loans, which originated before 2015, are repaid by 2020. As a result, there are relatively few defaults in this period as compared to all loans outstanding at that time.

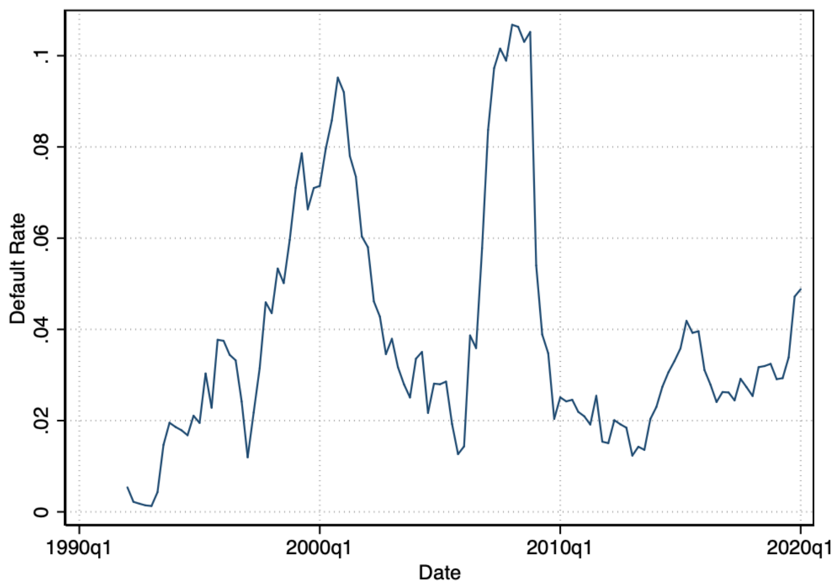
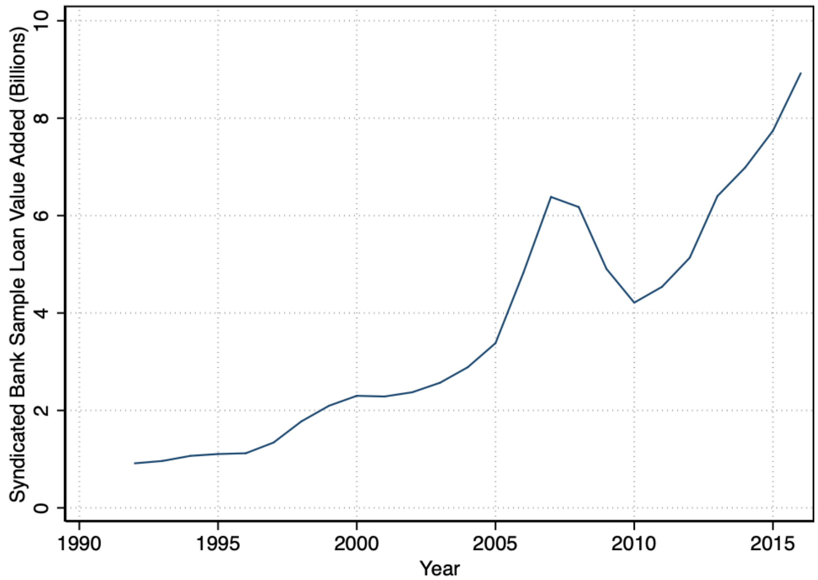


Figure A.8. Loan Dollar Value Added

Panel A plots the average value-added on outstanding in-sample loans.



Panel B plots the average value-added on extrapolated to all outstanding C&I loans covered by FRY-9C.

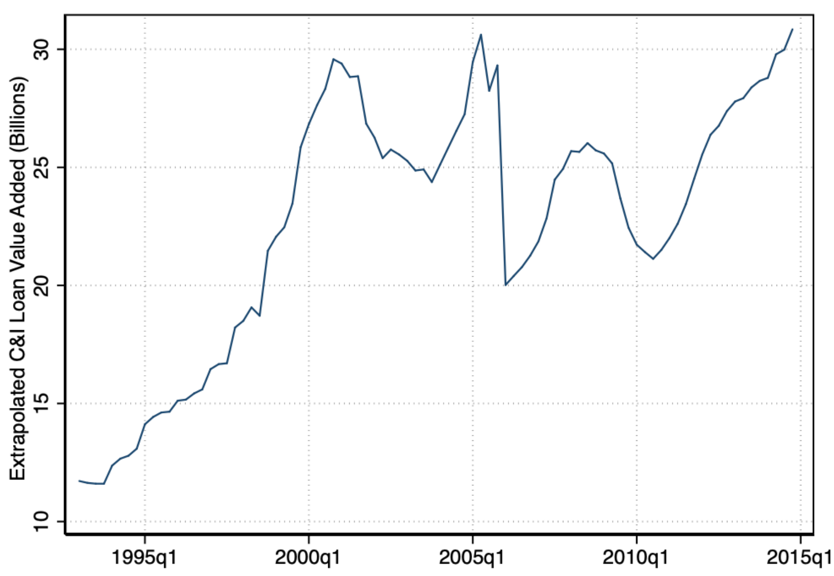


TABLE A.1. Rollover Benchmark Fund Example

Table A.1 gives a numerical example of the payoffs to a rollover benchmark portfolio given a hypothetical set of security returns. 'Period' is a hypothetical time since the benchmark was purchased. Starting Loan Balance is the hypothetical outstanding loan amount as a fraction of the original amount. 'Change Loan principal' is the fraction of the loan amount that is paid down at the end of the period. 'One Period Factor Return' is the hypothetical return to a public security that the benchmark fund invests in. 'Start rollover balance' is the amount of capital in the benchmark fund at the start of the period. 'Rollover Payout' is the cash-flow the rollover benchmark distributes at the end of the period.

Period	Starting Loan Balance	Change Loan Principal	One Period Factor Return	Start Rollover Balance	End Rollover Balance	Rollover Gain/Loss	Rollover Payout
1	1	0	1.05	1	1.05	0.05	0.05
2	1	0	1.03	1	1.03	0.03	0.03
3	1	0.25	1.02	1	1.02	0.02	0.27
4	0.75	0	1.01	0.75	0.7575	0.0075	0.0075
5	0.75	0.25	0.98	0.75	0.735	-0.015	0.235
6	0.5	0.25	0.99	0.5	0.495	-0.005	0.245
7	0.25	0	1.02	0.25	0.255	0.005	0.005
8	0	0	1.01	0	0	0	0

TABLE A.2. Gain Loan Benchmark Example

Table A.2 gives a numerical example of a gain benchmark portfolios given a set of security returns. Period is a hypothetical time since the benchmark was purchased. Starting Loan Balance is the hypothetical outstanding loan amount as a fraction of the original amount. Change Loan principal is the fraction of the loan amount that is paid down at the end of the period. 'One Period Factor Return' is the hypothetical return to a public security that the benchmark fund invests in. Start Gain Balance is the amount of capital in the benchmark fund at the start of the period. Cumulative Gain Payout is the cash-flow the risky gain benchmark distributes if bought and held until that period. Cumulative Gain rf Payout is the cash-flow the risk-free gain benchmark, investing in one-period treasury bonds, distributes if bought and held until that period. Long / short is the difference between these two portfolios.

Period	Starting Loan Balance	Change Loan Principal	One period Factor Return	Start Gain Balance	End Gain Balance	Change Gain Balance	Cumulative Gain Payout	Cumulative Gain Rf Payout	Long / Short
1	1	0	1.05	1.00	1.05	0.05	1.05	1.01	0.04
2	1	0	1.03	1.05	1.08	0.03	1.08	1.02	0.06
3	1	0.25	1.02	1.08	1.10	0.02	1.10	1.03	0.07
4	0.75	0	1.01	0.85	0.86	0.01	0.86	0.79	0.07
5	0.75	0.25	0.98	0.86	0.84	-0.02	0.84	0.80	0.05
6	0.5	0.25	0.99	0.59	0.59	-0.01	0.59	0.55	0.04
7	0.25	0	1.02	0.34	0.35	0.01	0.35	0.30	0.04
8	0	0	1.01	0.35	0.35	0.00	0.35	0.31	0.04

TABLE A.3. Sensitivity Analysis

This table reports how the main results change with different cash-flow and asset-pricing model assumptions. VW level corresponds to the baseline estimation using the 'Stocks + Bonds' model in Table 1.2. (H-L) indicates the reported risk-adjusted return is the difference between a portfolio of loans sorted by high and low levels of a given characteristic. Bootstrapped standard errors are in parenthesis when applicable (with the exception of elastic net, for which standard errors cannot be calculated). For elastic net point estimates, I add the mean discounted residuals (from Equation (17)) to the risk-adjusted profit because elastic net does not impose mean zero residuals.

Model/ Assumption	VW level	Constraints (H-L)	Relat. Inten. (H-L)	Proximity (H-L)	Lead Ret. (H-L)
Baseline	1.91	1.16	-0.84	-0.91	0.73
	(0.23)	(0.36)	(0.29)	(0.28)	(0.27)
Elastic Net	2.08	1.27	-0.51	-0.89	0.69
	(.)	(.)	(.)	(.)	(.)
LGD - 10%	1.58	1.18	-0.97	-0.99	0.70
	(0.24)	(0.35)	(0.31)	(0.23)	(0.37)
Loan Level LGD	1.97	1.05	-0.68	-0.79	0.68
	(0.21)	(0.28)	(0.26)	(0.15)	(0.31)
Alternative Amortization	1.95	1.12	-0.82	-0.83	0.55
	(0.20)	(0.28)	(0.26)	(0.19)	(0.30)
No Fee Impute	1.66	1.04	-0.81	-0.82	0.67
	(0.21)	(0.28)	(0.26)	(0.19)	(0.32)
Loan Level Estimation	1.50	0.74	-0.61	-0.57	0.55
	(0.13)	(0.18)	(0.12)	(0.15)	(0.10)
P-S Liq Factor	2.08	1.20	-0.71	-0.84	0.71
	(0.24)	(0.27)	(0.18)	(0.21)	(0.33)
VW Cross-Section	(.)	1.20	-1.20	-0.89	0.54
	(.)	(0.45)	(0.43)	(0.38)	(0.3)

TABLE A.4. Expense Ratio Sensitivity Analysis

Table A.4 reports how the estimated commercial lending expense ratio using the methodology of Hanson et al. (2015) change under under alternative assumptions. The baseline row shows the estimates from the main text using the entire FRY-9C bank holdings sample. Each row reports how the average expense ratio changes when changing the filters for the sub-sample of banks or alternative estimate procedures.

Assumption	Total Non Interest	Staff Comp	Other Opex
Baseline Commercial Loan	164	109	55
Drop Banks with Any Trading	172	104	68
Also Impose Large Bank Size	130	104	26
Avg. Expense For All Types of Loans	203	112	91
Ave. Expense for Bank without Deposits	183	97	86

TABLE A.5. Promised Yield and Implied Credit Spread

	VW	EW
Promised return (discounted at rf) (no default)	3.30	3.90
Risk-adjusted return	1.90	2.70
Implied credit spread	1.40	1.20

TABLE A.6. Impact of Revolver in Loan Package

	ψ
No Revolver in Package	2.376***
	(0.235)
Revolver in Package	2.646***
	(0.187)
Difference	0.271
	(0.324)
Number of Loans:	8116

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.7. Impact of Opacity (Pre-Crisis)

	ψ
Low Opacity	1.487***
	(0.255)
High Opacity	2.813***
	(0.240)
Difference	1.325***
	(0.345)
Number of Loans:	5908

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.8. Impact of Bond Issuance

	ψ
No Bond Outstanding	2.783***
	(0.139)
Bonds Outstanding	1.889***
	(0.236)
Difference	-0.895***
	(0.307)
Number of Loans:	5914

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.9. Bank Loan Market Power

Table A.9 reports the mean risk-adjusted returns, ψ, for loan portfolios sorted on measures of market power. I form sets of equal-weighted portfolios of loans sorted by loan industry Herfindahl index and loan industry-state Herfindahl index. Panel A reports the risk-adjusted returns, ψ, to these portfolios. I estimate risk factor loadings and ψ separately for each set of portfolios, using the 'Stocks + Bonds' model in Table 1.2. 'H-L' reports the mean difference between the high and low opacity portfolios and 'T-stat' reports the t-statistic for this difference. Panel B reports the mean characteristics of the loans in each portfolio. Standard errors are computed using the Driessen et al. (2012) non-parametric block bootstrap procedure.

	ψ Sorted by Market Power				
Risk-Adjusted Returns	Low	2	3	High	H−
Loan Industry HHI	2.56***	1.87***	2.82***	2.92***	0.36
	(0.18)	(0.26)	(0.26)	(0.22)	(0.31)
Loan Industry State HHI	2.55***	2.47***	2.40***	2.97***	0.42
	(0.22)	(0.19)	(0.27)	(0.26)	(0.35)
	Mean Characteristic Sorted by Market Power				
Measure of Market Power	Low	2	3	High	H−
Loan Industry HHI	0.03	0.03	0.04	0.07	0.04
	(0.00)	(0.00)	(0.00)	(0.00)	
Loan Industry State HHI	0.04	0.07	0.12	0.34	0.30
	(0.00)	(0.00)	(0.01)	(0.02)	

Bootstrapped standard errors clustered by loan in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.10. Sort by Spreads

	ψ
Low Spread	2.000***
	(0.127)
High Spread	3.100***
	(0.311)
Difference	1.099***
	(0.329)
Number of Loans:	8157

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.11. Loan Covenant Tightness

	ψ
Low Covenant Tightness	2.092***
	(0.301)
High Covenant Tightness	2.764***
	(0.157)
Difference	0.672***
	(0.234)

Bootstrapped standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

B. Data Appendix to Chapter 2: Did Banks Pay Fair Returns to Taxpayers on TARP?

F. Example Calculations

JP Morgan received a TARP preferred equity investment of $25 billion on October 28, 2008. As per the TARP CPP term sheet[30], the original (earliest) repayment date was October 28, 2011. JP Morgan repaid the TARP investment in full, however, on June 17, 2009. In addition to returning the full investment amount of $25 billion, JP Morgan paid 5% per annum cumulative quarterly dividends (as per the term sheet) resulting in $795 million in dividend payments to the Treasury. The preferred equity investment also granted the Treasury 88,401,697 warrant shares (15% of the preferred equity investment) to purchase new issues of JP Morgan stock on October 28, 2018 at an exercise price of $42.24 (the 20 day moving average of the stock price around the initial investment amount). On December 10 2009, the Treasury sold these warrants to market participants at auction for a total of $950 million or $10.75 a share. The annualized rate of return from the TARP investment in JP Morgan is 10.95%.

To calculate a benchmark return for JP Morgan, we compute the annualized return of investing in a market index from October 28, 2008 to December 10 2009, the investment horizon of the TARP preferred equity investment. Investing in the S&P US Preferred Stock Index over this horizon would have earned an annualized return of 48.96%. The benchmark index subsidy is simply the difference from the TARP return, 38.0%. Investing in JP Morgan preferred equity over the same time horizon would have earned an annualized return of 35.77%. The same bank subsidy is therefore 24.82%.

[30] Available at http://www.treasury.gov/press-center/press-releases/Documents/document5hp1207.pdf

F. TARP Loss Example

It is possible that TARP makes a negative return on its investment. This happens in the case that a bank fails to repay the preferred equity principal and/or TARP sells the preferred equity at a loss to market participants. An example is Northern States Financial Corporation, which received a $17.2 million investment from TARP in 2009. After five years, TARP sold the preferred equity at a loss for $6 million. Including dividend payments, the total cash back from this investment was only $6.42 million. The warrants became worthless and generated no proceeds.

In some cases, TARP effectively earns an annualized internal rate of return of -100%. One example of this is Midwest Banc Holdings which closed and went into receivership of the Federal Deposit Insurance Corporation (FDIC). Thus the IRR was effectively -100%.

F. Duration Risk

A potential concern with the analysis so far is that traded preferred equity securities may not be directly comparable to TARP investment due to the differences in the duration of these investments. The weighted average life of the TARP investments in our same bank preferred equity sample is 1.18 years. The preferred equity used as the benchmark, however, has an average life of 43.35 years.[31] Since these two investments have a difference of 42.17 years in duration, the estimated subsidy might reflect differences in returns due to duration risk. We check how much duration risk is affecting the subsidy estimate by calculating the return to a 30-year Treasury bond over the same 1.18 year period as our same bank preferred equity investments.[32] We find an annualized return of -3.39% on 30-year Treasury bonds over this period. This indicates that the previously reported subsidy measure would, in fact, be larger once accounting for the differences in duration risk between the TARP investment and traded preferred equity.

[31] For perpetual preferred equity we assume a life of 50 years. Since many of these preferred equity securities are callable, the effective maturity may be shorter.

[32] A 30-year Treasury bond is the closest available market benchmark to capture the 42.17 year difference in duration of the two investments.

F. Construction of the Replicating Portfolio Benchmark

Our replicating portfolio invests 90% in the bank's plain preferred equity and 10% in the Warrants. Preferred equity returns are computed as discussed in the paper. To estimate the return on the warrant's part of the replicating portfolio, we use a valuation model that closely resembles the Treasury's valuation methodology to estimate the fair market value of the warrants each day from the date of TARP investment till the day of warrant disposal. Based on these fair values we compute daily returns to the warrants. The benchmark return is simply the weighted average return of the portfolio.

Warrants are valued as an American Call Option on a dividend paying stock. Following the Treasury's model, we use a bionomial approximation to the Black-Scholes model for this valuation. The estimation of the model requires a number of assumptions on the inputs as well as valuation technique used to get these estimates. We closely follow the methodology of the Treasury in making these assumptions and modeling choices. Below we list our assumptions, and the underlying rationale, for each input of the model.[33]

- Stock Price (S): We obtain the daily stock price comes from the CRSP dataset. We adjust the stock price as well as the variables below to account for any corporate actions/stock splits.

- Strike Price (K): At the time of the investment, the strike price for warrants was set at a 20-day moving average of the company's common stock's price measured two weeks before the investments. The strike price was adjusted downward following any dividend payment amount in excess of the dividend per share at the time the strike price was set. We follow the same methodology to compute the strike price for each bank's warrant.

- Risk-free rate (r): The Treasury uses the yield on a risk-free bond that matches the remaining maturity of the warrant. We use the risk-free rate on 10-year treasury as our input for 'r', since most of these warrants had a remaining maturity of 7-10 years

[33] Available at: https://www.treasury.gov/initiatives/financial-stability/TARP-Programs/bank-investment-programs/cap/Pages/default.aspx

during our computation period.

- Dividend Payout (y): We consider the annual dividend yield computed using the bank's most recent quarterly dividend payment and the stock price on a given day.

- Volatility (σ): The Treasury uses both the historical volatility and implied volatility to construct a 10-year forward volatility curve, and takes the average of these volatilities as the input to the valuation model. The initial part of the forward volatility curve comes from the implied volatility of traded option, the later part comes from 10-year average historical volatility. In our valuation model, we use both the implied volatility for the longest dated traded option available in the OptionMetric database. We compute the historical volatility using common equity returns from CRSP. Our base model uses the average of the two volatility as the input for σ.

- Dilution effects for warrants: Warrants are different from standard call options in the sense that if the warrants are exercised then the company has to raise new shares. The Treasury makes no adjustments to the Black-Scholes valuation model for the resulting dilution. We follow the same approach. The rationale behind this non-adjustment is that the stock market rationally anticipates these effects and hence the current stock price of the company, a key input to the valuation model, already accounts for this effect.

[See Table A.12]

[See Table A.13]

[See Table A.14]

[See Table A.15]

[See Table A.16]

[See Table A.17]

[See Figure A.9]

[See Figure A.10]

[See Figure A.12]

[See Figure A.13]

F. Figures and Tables

Figure A.9. TARP Investment v. Same Bank Preferred Equity With Warrant

Figure A.9 compares a bank's TARP CPP Return to a replicating portfolio consisting of a bank's preferred equity and warrants. The portfolio assigns a 90% weight to preferred equity claims and 10% weight to the warrant.

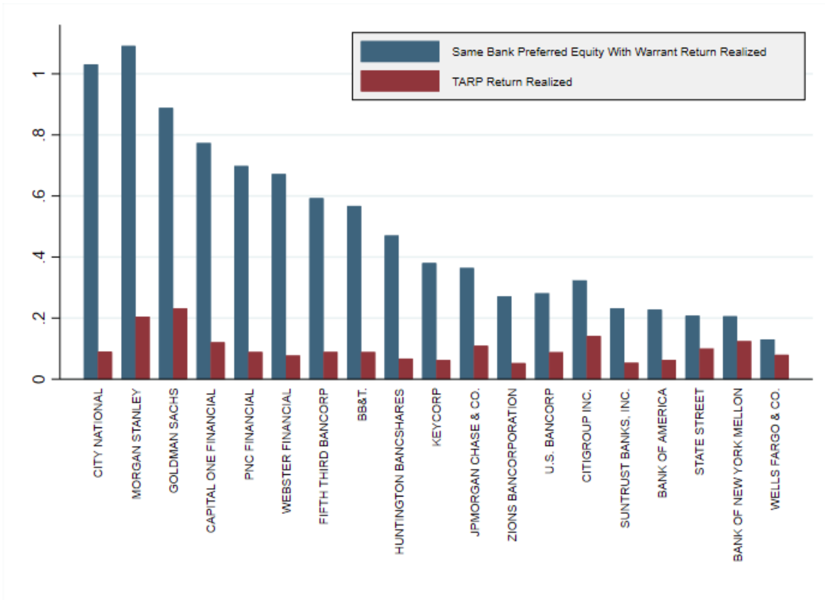


Figure A.10. Histogram of TARP Investment NPVs

Figure A.10 plots a histogram distribution of 'Investment NPV' using the full sample of 653 banks. NPV is calculated by discounting back the net cash flows from the TARP investments using the cumulative returns on the S&P US Preferred Stock Index. Net cash flows are normalized by each bank's total TARP investment amount.

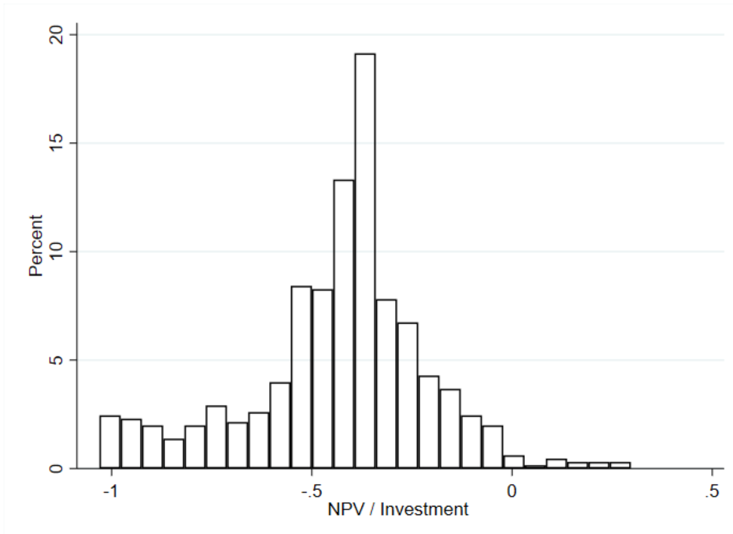


Figure A.11. Scaled NPV of TARP Investments

Figure A.11 plots individual banks' 'Investment NPV'. NPV is calculated by discounting back the net cash flows from the TARP investments using the cumulative returns on the same bank's preferred equity. The NPV is scaled by each bank's total TARP investment amount to obtain the NPV on a per dollar basis.

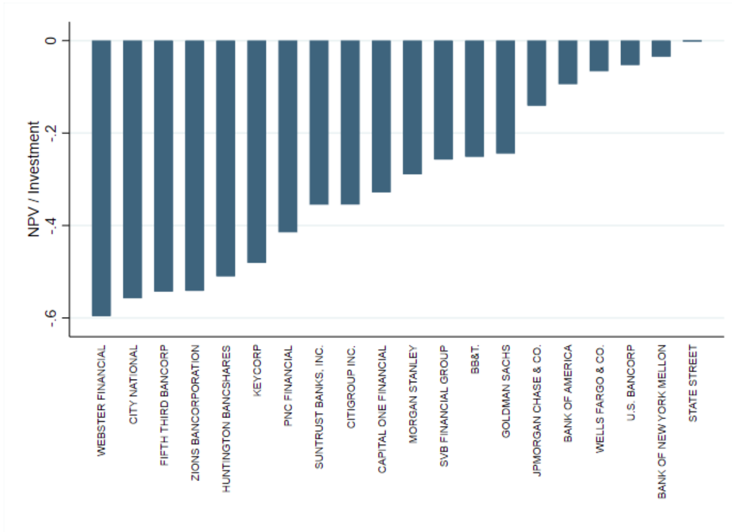


Figure A.12. Dollar NPV of TARP Investments

Figure A.12 plots banks' 'Dollar NPV'. Dollar NPV is calculated by discounting back the net cash flows from the TARP investments using the cumulative returns on the same bank's preferred equity.

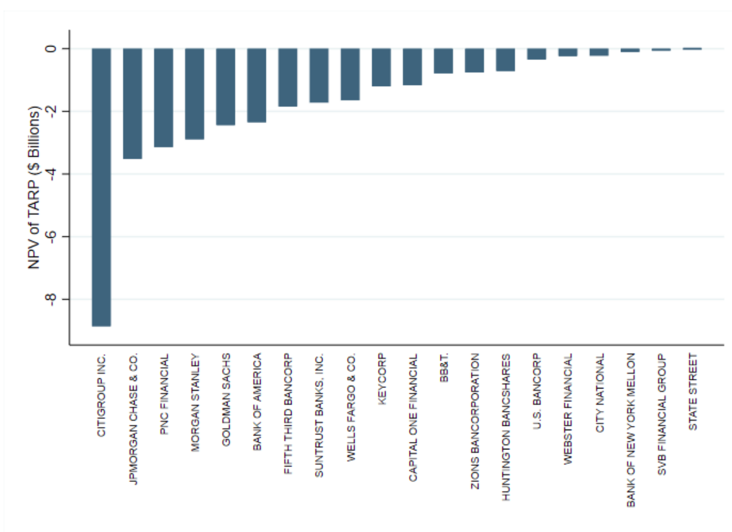


Figure A.13. Bid-Ask Half Spread of Bank Preferred Equity

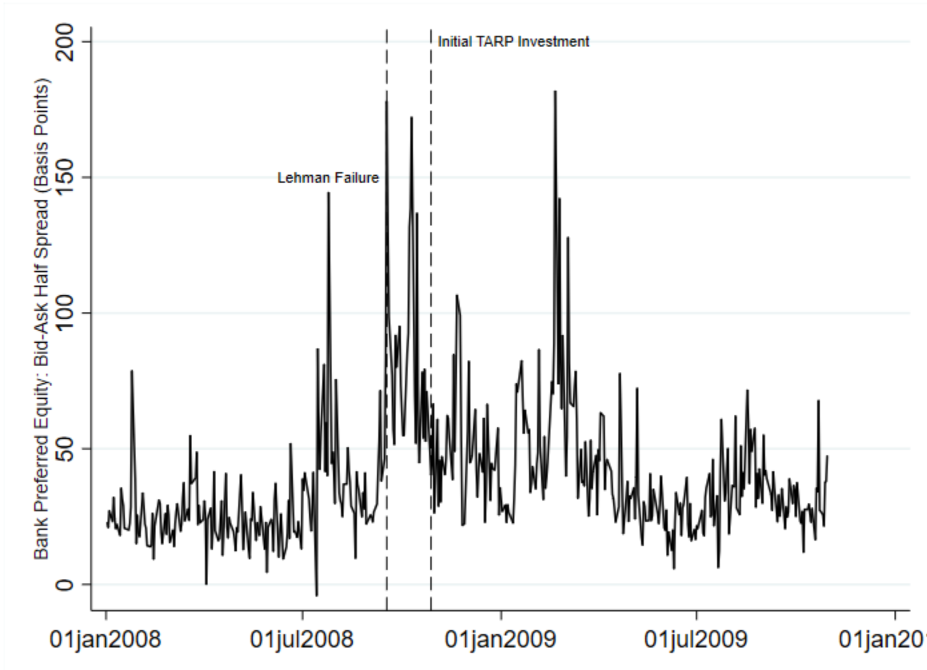


TABLE A.12. Sample Formation

Sample Step	Total	Investment Amount ($ Billions)
All Banks Participating in TARP CPP	707	204.9
Original Investment Type Preferred Equity (Full Sample)	653	204.3
Covered by 2009Q1 FRY-9C Report (BHC Subsample)	196	191.0
Individual Bank Preferred Equity Return Available (Same Bank Subsample)	20	160.5

TABLE A.13. Cross-Sectional Variation in Economic Subsidies

Table A.13 relates the economic magnitude of TARP subsidies to bank risk characteristics. The table regresses the economic subsidy measured by NPV on a bank's CAPM beta and volatility. NPV is calculated by discounting back the net cash flows from TARP investments using the cumulative returns on the S&P US Preferred Stock Index. 'NPV / Investment' and 'NPV / Assets' normalizes 'Dollar NPV of TARP' using the TARP investment amount and total bank assets, respectively. Note that a negative NPV corresponds to a positive TARP subsidy. Beta is a bank's common equity beta estimated from a monthly CAPM (using the CRSP VW index) over 2006Q1 to 2009Q1. Volatility is a bank's common equity volatility estimated using monthly returns over 2006Q1 to 2009Q1. Results are robust to using an unannualized version of the TARP Subsidy as the dependent variable. Standard errors are clustered at the bank level.

	NPV / Assets		NPV / Investment	
	(1)	(2)	(3)	(4)
Beta	-0.002**		-0.088***	
	(-2.37)		(-2.87)	
Volatility		-0.012***		-0.446***
		(-5.44)		(-4.93)
Log(Assets)	0.001***	0.001***	0.035***	0.036***
	(3.94)	(4.29)	(5.27)	(5.92)
Constant	-0.020***	-0.017***	-0.875***	-0.759***
	(-5.86)	(-5.00)	(-8.47)	(-7.77)
Observations	196	196	196	196
R^2	0.031	0.069	0.096	0.172

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.14. Bank Bond Index Benchmark Returns

Table A.14 presents the results comparing TARP returns to bank bond benchmark indices. TARP Return Realized is calculated as the annualized internal rate of return that sets the NPV of TARP cash flows to zero. Bloomberg Bond Index Return Realized is the annualized rate of return from investing in the Bloomberg Bond Index for the same investment horizon as that bank's TARP investment. Individual Bank Senior Bond Return Realized is computed using the same bank's senior bond returns and the same investment horizon as that bank's TARP investment. TARP Subsidy is the difference between a bank's benchmark index return and TARP's return. Panel A presents the returns from investing in TARP and benchmark portfolios. EW Return is the equal-weighted return across banks. VW Return is the value-weighted return using the original TARP investment amount as the weight. Panel B presents the return distribution for the TARP and benchmark returns.

Panel A: TARP and Bank Bond Index Returns

	Full Sample		BHC Sample	
	EW Return	VW Return	EW Return	VW Return
TARP Return Realized	-0.01	0.09***	0.02	0.09***
Bloomberg Barclays IG Bond Fin. Inst. Return Realized	0.12***	0.20***	0.13***	0.21***
Bloomberg Barclays BBB Bond Return Realized	0.16***	0.27***	0.18***	0.28***

Panel B: Return Distribution

	Mean	SD	Min	P25	P50	P75	Max	N
TARP Return Realized	-0.01	0.22	-1.00	0.03	0.06	0.07	0.34	653
Bloomberg Barclays IG Bond Fin. Inst. Return Realized	0.12	0.05	-0.23	0.10	0.12	0.14	0.45	653
Bloomberg Barclays BBB Bond Return Realized	0.16	0.06	0.04	0.11	0.15	0.18	0.41	653

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.15. Same Bank Preferred Equity (Mutliple Issues)

Table A.15 presents the results using all outstanding preferred equity returns of the same bank. TARP Return Realized is calculated as the annualized internal rate of return that sets the NPV of TARP cash flows to zero. Individual Bank Preferred Equity Return Realized is computed using the same bank's preferred equity returns and the same investment horizon as that bank's TARP investment. Individual bank preferred equity returns are taken from Refinitiv Datastream using the all outstanding issue at the time of the TARP investment. For each bank, we take a weighted average of each issue's returns using the issue size as the weight. Subsidy is the difference between a bank's preferred equity return and TARP's return. EW Return is the equal-weighted return across banks. VW Return is the value-weighted return using the original TARP investment amount as the weight. The twenty banks for which preferred equity returns are available comprise 78% of the TARP CPP's $205 billion investment.

	EW Return		VW Return	
TARP Return Realized (Same Bank Sample)	0.10***	(9.66)	0.11***	(9.90)
Individual Bank Prefered Equity Return Realized	0.43***	(7.60)	0.38***	(8.25)
TARP Subsidy (Difference)	0.33***	(6.22)	0.27***	(6.77)

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.16. Benchmark Returns and Policy Uncertainty

Table A.16 presents TARP subsidy estimates using forward-shifted investment horizons to form benchmarks. TARP Return Realized is calculated as the annualized internal rate of return that sets the NPV of TARP cash flows to zero. In Panel A, the benchmark return is the annualized return from investing in the S&P US Preferred Stock Index for the same investment horizon as a bank's TARP investment. In Panel B, the benchmark return is the annualized return from investing in the same bank's preferred equity for the same investment horizon as that bank's TARP investment. TARP Subsidy is the difference between a bank's benchmark index return and TARP's return. In the '6M Shift' Column, the investment horizon is shifted forward by 6 months holding the investment duration fixed. The investment horizon is similarly adjusted forward by 9 months and 1 year in subsequent columns. EW Return is the equal-weighted return across banks. VW Return is the value-weighted return using the original TARP investment amount as the weight. Individual bank preferred equity returns are taken from Refinitiv Datastream using the most recent preferred equity issue prior to 2008 with trading data available until the end of the original TARP maturity.

Panel A: Preferred Equity Index

	6M Shift		9M Shift		1Y Shift	
	EW Return	VW Return	EW Return	VW Return	EW Return	VW Return
TARP Return Realized	-0.01	0.09***	-0.01	0.09***	-0.01	0.09***
S&P Preferred Stock Index Return Realized	0.14***	0.41***	0.10***	0.17***	0.08***	0.16***
TARP Subsidy	0.15***	0.32***	0.11***	0.08***	0.09***	0.06***

Panel B: Same Bank Preferred Equity

	EW Return	VW Return	EW Return	VW Return	EW Return	VW Return
TARP Return Realized	-0.01	0.09***	-0.01	0.09***	-0.01	0.09***
Bank Preferred Equity Return Realized	0.49***	0.47***	0.26***	0.24***	0.22***	0.19***
TARP Subsidy	0.39***	0.36***	0.16***	0.13***	0.12***	0.08***

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.17. Counterfactual Sensitivity Analysis

Table A.17 performs a sensitivity analysis by recalculating TARP NPV after changing contractual features of TARP investments holding fixed the realized return series. 'Baseline NPV' is NPV of the TARP investment reported earlier. In Panel A, 'NPV with Warrant HTM' is the NPV recalculated using the payoff the Treasury would have received if they held the warrant to maturity instead of disposing it early. 'NPV with X% Warrant HTM', is the NPV if the Treasury increased the fraction of warrants held from 15% of principal to X%. In Panel B, 'NPV X% Coupon' is the PME if the Treasury increased the preferred equity coupon from 5% to X%. Standard errors are clustered at the bank level.

Panel A: Warrant Sensitivity Analysis

	EW Return		VW Return	
Baseline NPV	-0.38***	(-22.67)	-0.26***	(-22.05)
NPV with Warrant HTM	-0.33***	(-17.93)	-0.24***	(-20.35)
NPV with 30% Warrant HTM	-0.26***	(-10.19)	-0.20***	(-14.70)
NPV with 45% Warrant HTM	-0.18***	(-5.42)	-0.17***	(-10.07)
NPV with 60% Warrant HTM	-0.11**	(-2.50)	-0.13***	(-6.59)
NPV with 80% Warrant HTM	-0.01	(-0.10)	-0.08***	(-3.27)
NPV with 100% Warrant HTM	0.09	(1.41)	-0.03	(-0.97)
Observations	107		107	

Panel B: Coupon Sensitivity Analysis

	EW Return		VW Return	
Baseline NPV	-0.44***	(-48.87)	-0.26***	(-44.64)
NPV 10% Coupon	-0.37***	(-39.95)	-0.23***	(-41.12)
NPV 20% Coupon	-0.25***	(-23.29)	-0.17***	(-30.69)
NPV 30% Coupon	-0.13***	(-10.00)	-0.11***	(-17.98)
NPV 40% Coupon	-0.00	(-0.11)	-0.04***	(-6.44)
Observations	653		653	

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

C. Data Appendix to Chapter 3: Why Do Banks Hide Losses?

[See Figure A.14]

[See Table A.18]

Tobit Underreporting Dependent Variable: As described in the main text, the Tobit dependent variable is the log of (Actual NPL - 0.15 x Incremental NPL)/Reported NPL[34]. The intuition behind this measure is that it captures the minimum NPL a bank could report before having to disclose as per the RBI mandate. Since each bank has a different minimum NPL threshold, the measure standardizes the cutoff for every bank in the sample. For example, in 2016, ICICI Bank had 2.62 billion Reported NPL, 1.66 billion Incremental NPL, and 3.13 billion Actual NPL. As per the regulation, the minimum NPL ICICI Bank could report before being required to disclose is: Actual NPL minus 15% of incremental NPL = (3.13 - .15 x 1.66)= 2.88 billion. Since ICICI Bank reported less than this (2.62), it was required to disclose the true amount. Therefore, the dependent variable for Tobit is log[(3.13 - .15 x 1.66)/ 2.62] = .095. In general, the Tobit dependent variable has the following properties: If a bank underreports enough to exceed the 15% threshold, then log transformed variable is positive. If a bank underreports exactly at the 15% threshold amount, then log transformed variable is zero. If a bank underreports less than 15% threshold amount, then log transformed variable is negative and censored.

Shareholding Variables: All shareholding variables are annual and measured on March 31st, the end of the fiscal year for all banks in India.

[See Table A.19]

[See Figure A.15]

[34] Incremental NPL is the subset of NPL that only became non-performing in the most recent reporting period

[See Table A.20]

[See Table A.21]

[See Table A.22]

F. Figures and Tables

TABLE A.18. Variable Descriptions

Variable	Description	Source
GNPA Underreporting	Log(Actual NPL/Reported NPL)	Hand Collected
Provision Underreporting	Log(Actual Provision/Reported Provisions)	Hand Collected
Remuneration	Log of Total Remuneration awarded to the CEO	Hand Collected & Prowess
GNPA	Gross Non-Performing Assets / Total Assets	RBI Statistics
Capital	Tier 1 Capital Ratio	RBI Statistics
Net Profit	Net Profits/Total Assets	RBI Statistics
Lev.	(Total Debt + Total Deposits)/Total Assets	Prowess
Market Cap	Closing Price $\times$ Shares Out	Prowess
Tobin Q	Book Value/Market Cap	Prowess
% FII	FII Shares/Total Number of Shares	Prowess
% Inst.	Inst. Shares/Total Number of Shares	Prowess
% DII	DII Shares/Total Number of Shares	Prowess
% RBI	RBI Shares/Total Number of Shares	Prowess
Average % FII	FII Shares/Number of FII Investors	Prowess
ROA	Return on Assets	RBI Statistics
ROE	Return on Equity	RBI Statistics
GNPA Ratio	Gross Non-Performing Assets / Advances	RBI Statistics
Board Size	Number of Directors on Board	Prowess
RBI Mem.	Indicator if RBI member serves on the Board	Prowess
CEO Chair	Indicator if CEO is chair of the Board	Prowess
% Outsiders	Percentage of Independent Board Members	Prowess
% Audit Board Outsiders	Percentage of Independent Members on Audit Board	Prowess

TABLE A.19. Event Study

The Table reports cumulative abnormal returns (CAR's) around announcement of bank divergences. Expected returns are calculated using the market model (Using the India MSCI Value-Weighted Index) in a (-120,-30) estimation window. Divergences in FY2016 were announced upon the release of the 2017 annual report for all banks meeting the minimum required reporting threshold.

	2016 Divergent Banks	2016 Non-Divergent Banks
Event Window	CAR	CAR
Constant	-0.025**	0.001
	(-2.67)	(0.09)
Constant	-0.060***	0.011
	(-3.83)	(0.48)
Constant	-0.039***	-0.015
	(-4.44)	(-0.82)
Observations	23	12

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Figure A.14. YesBank NPL Disclosure

18.5.6.3 DIVERGENCE IN ASSET CLASSIFICATION AND PROVISIONING FOR NPAS – (REF DBR. BP.BC.NO. 63/ 21.04.018/2016-17 DATED APRIL 18, 2017)

₹ in millions

Sr. No.	Particulars	
1	Gross NPAs as on March 31, 2016 as reported by the Bank	7,489.81
2	Gross NPAs as on March 31, 2016 as assessed by RBI	49,256.81
3	Divergence in Gross NPAs (2-1)	41,767.00
4	Net NPAs as on March 31, 2016 as reported by the Bank	2,844.74
5	Net NPAs as on March 31, 2016 as assessed by the RBI	36,031.49
6	Divergence in Net NPAs (5-4)	33,186.75
7	Provision for NPAs as on March 31, 2016 as reported by the Bank	4,645.07
8	Provision for NPAs as on March 31, 2016 as assessed by RBI	13,225.32
9	Divergence in provisioning (8-7)	8,580.25
10	Reported Net Profit after Tax (PAT) for the year ended March 31, 2016	25,394.47
11	Adjusted (notional) Net Profit after Tax (PAT) for the year ended March 31, 2016 after taking into account the divergence in provisioning	19,783.84

The table above is in conformity with RBI circular issued on April 18, 2017 and as per approval from Board of Directors at its Board meeting held on April 19, 2017, the audited financial statements of the Bank for the year ended March 31, 2017, duly incorporates the current impact of divergences observed recently by RBI

TABLE A.20. Interval Regression

Dependent variable is log(Actual NPL/Reported NPL). Interval regression bounds the amount underreporting of banks that did disclose underreporting between 0% and 15% of incremental NPL. $\%FII$ and $\%DII$ are the percentages of bank equity owned by foreign and domestic institutional investors. $Private$ an indicator variable whether less than 50 % of the bank is owned by the state. $Remun$ is the log of total remuneration awarded to a bank's CEO in the year of underreporting. Underreporting is observed in years 2016 and 2017. Standard errors are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)
$\%FII$	0.247^{**}		0.255^{**}	0.011	0.111^{*}
	(2.22)		(2.24)	(0.17)	(1.73)
$\%DII$		0.016	0.041		
		(0.31)	(0.78)		
$Private$				0.069	
				(0.37)	
$Private \times \%FII$				0.334^{**}	
				(2.33)	
$Remun.$					0.032
					(0.64)
$Remun. \times \%FII$					0.132^{*}
					(1.96)
$Capital$	-0.121^{*}	0.051	-0.132^{*}	-0.127^{*}	-0.095^{*}
	(-1.74)	(1.52)	(-1.84)	(-1.92)	(-1.65)
$Log(Assets)$	0.003	-0.018	-0.007	-0.014	-0.031
	(0.15)	(-0.78)	(-0.31)	(-0.31)	(-1.01)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	73	73	73	73	61

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE A.21. Robustness - Control Variables

Table A.21 presents earlier models with richer control variables. OLS Dependent variable is log(Actual NPL/Reported NPL). In the Tobit panel, the dependent variable is log of Actual NPA - 0.15 x Incremental NPA)/Reported NPA. $\%FII$ is the percentage of bank equity shares owned by foreign institutional investors. *Remun* is the log of total remuneration awarded to a bank's CEO. *Capital* is the Tier 1 Capital Ratio. $GNPA$ is the level of gross non-performing assets scaled by total assets. $TobinQ$ is bank book value divided by market value of bank. All explanatory variables are measured in 2015 (prior to underreporting disclosures). All continuous explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Underreporting is observed in years 2016 and 2017. Columns (1), (2), and (3) present OLS results conditional on a bank reporting divergences. Columns (4), (5), and (6) present results from a Tobit regression using the sample of all banks in 2016 and 2017. Observations are censored below by the 15% minimum GNPA required to report. Standard errors are clustered at the bank level.

	OLS			Tobit		
	(1)	(2)	(3)	(4)	(5)	(6)
$\%FII$	0.215*	-0.151**	-0.001	0.316**	-0.609***	0.043
	(2.00)	(-2.33)	(-0.03)	(2.27)	(-2.95)	(0.46)
$Private$		0.379*			1.031***	
		(1.82)			(3.18)	
$Private \times \%FII$		0.431**			0.925***	
		(2.41)			(3.17)	
$Remun.$			0.201**			0.174*
			(2.68)			(1.88)
$Remun. \times \%FII$			0.165**			0.240**
			(2.37)			(2.65)
$Log(Assets)$	0.027	0.156*	0.034	0.030	0.285***	0.012
	(0.53)	(1.97)	(0.68)	(0.39)	(2.71)	(0.19)
$Capital$	-0.087	-0.079	0.021	-0.284**	-0.271**	-0.160*
	(-0.89)	(-0.91)	(0.33)	(-2.22)	(-2.53)	(-1.74)
$GNPA$	-0.036	-0.042	-0.031	-0.133	-0.165**	-0.120*
	(-0.88)	(-1.30)	(-1.17)	(-1.45)	(-2.14)	(-1.77)
freefloat_marketcap	-0.069	-0.151**	-0.211**	-0.050	-0.188**	-0.197**
	(-1.06)	(-2.24)	(-2.24)	(-0.78)	(-2.49)	(-2.11)
$Neg\ Profits$	0.058	0.013	0.021	0.022	0.031	-0.038
	(0.78)	(0.17)	(0.26)	(0.16)	(0.26)	(-0.29)
$Growth$	0.166	0.117	0.066	-0.044	-0.078	-0.161**
	(1.51)	(1.21)	(0.68)	(-0.59)	(-1.12)	(-2.32)
$TobinQ.$	0.080	0.084	0.025	0.050	0.062	0.006
	(1.51)	(1.43)	(0.37)	(1.18)	(1.37)	(0.12)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52	52	46	72	72	60
R^2	0.582	0.659	0.704			
Pseudo R^2				0.298	0.481	0.463

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

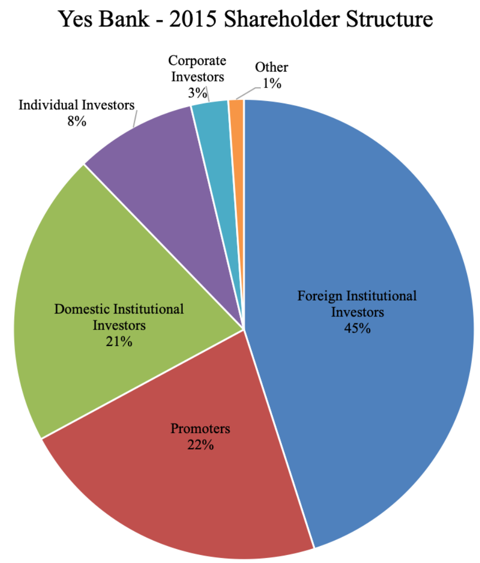
TABLE A.22. IV Placebo Test

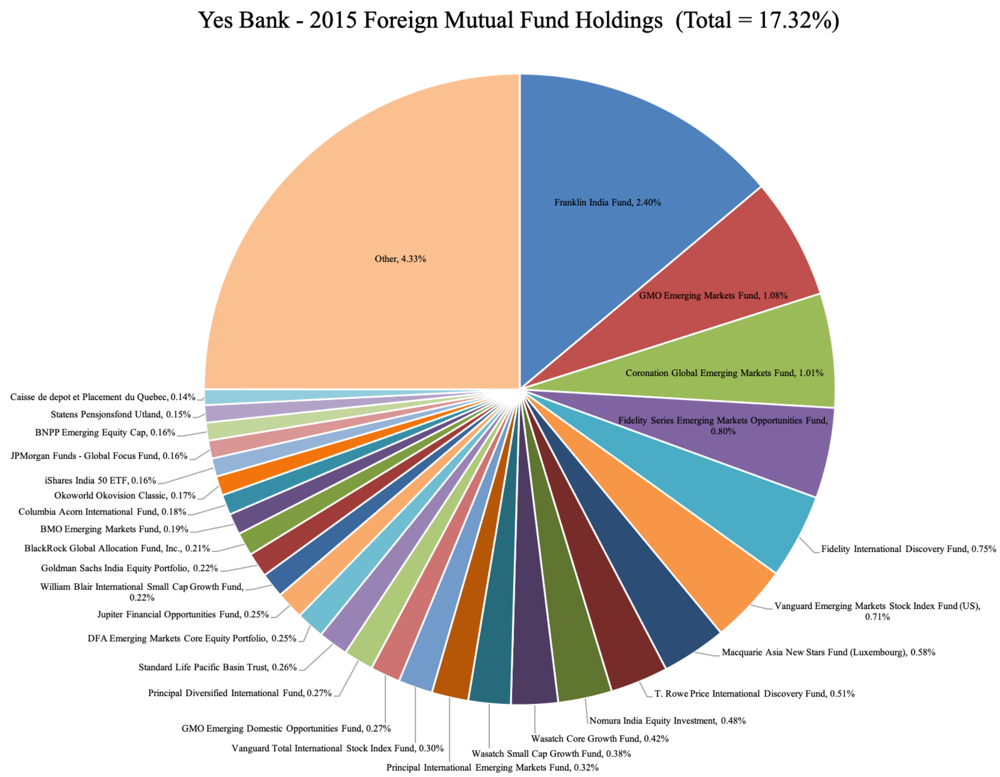
Table A.22 imitates the first stage of the IV regression using $\%DII$ instead of $\%FII$ as the dependent variable. The instrument, $MSCI$, is defined as 1 if the bank was included in the MSCI India domestic index in 2015 and 0 otherwise. $\%FII$, and $\%DII$ are the percentage of bank equity shares held by foreign institutional, and domestic institutional investors. *Capital* is the Tier 1 Capital Ratio. *Capital* is the Tier 1 Capital Ratio. $MarketCap$ is the market capitalization of a bank's common equity; $FreeFloatMarketCap$ is computed only using free floating shares. *Liquidity* 12-month average trading value ratio as defined by MSCI. $ForeignRoom$ is the maximum % of foreign share allowed minus existing foreign investment. All explanatory variables are measured in 2015 (prior to underreporting disclosures). All continuous explanatory variables are standardized such that coefficients can be interpreted as the effect from a one s.d. increase. Underreporting is observed in years 2016 and 2017. Standard errors are clustered at the bank level.

	OLS		Tobit	
$MSCI$	-0.226	-0.140	-0.288	0.053
	(-0.54)	(-0.28)	(-0.74)	(0.10)
Capital	0.094	0.515	0.155	0.488
	(0.39)	(1.39)	(0.63)	(1.53)
$Log(Assets)$	0.271***	0.416	0.264***	0.823
	(2.91)	(0.79)	(2.79)	(1.45)
$FreeFloatMarketCap$		-0.252		-0.265
		(-1.04)		(-1.03)
Liquidity		-0.009		0.064
		(-0.04)		(0.29)
$MarketCap$		-0.073		-0.356
		(-0.16)		(-0.68)
$ForeignRoom$		-0.275		0.210
		(-0.67)		(0.46)
Constant	-0.002	-0.002	0.078	-0.003
	(-0.01)	(-0.01)	(0.35)	(-0.02)
Year FE	Yes	Yes	Yes	Yes
Observations	53	52	73	72
R^2	0.233	0.256	0.141	0.220
F	0.295	0.078	0.541	0.010

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure A.15. Yes Bank Shareholder Structure





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