Bank Monitoring with On-Site Inspections

January 9, 2023

Using a proprietary transaction-level database of nearly 30,000 multiple-draw construction loans, we empirically examine determinants and effects of bank monitoring through on-site inspections. Consistent with theoretical predictions, banks trade off monitoring with favorable origination terms. Monitoring is also less frequent when the bank has a prior relationship with the borrower, suggesting information transfers across projects. Textual analysis shows that negative inspection reports are associated with a greater likelihood of banks denying draw requests, indicating that the information collected through monitoring is important for decision-making. Finally, we provide a comprehensive analysis of construction loan default and show that monitoring decreases default.

1. Introduction

As increasing amounts of lending activity migrate away from banks and into non-bank finance companies,[1] only a few categories of loans remain largely in the hands of modern banks. Using Call Report data, Figure 1 shows that lending in commercial real estate (CRE) loans has increased as a share of bank balance sheets over time, with the largest proportional increases occurring in small banks. It is well established that CRE lending is inherently risky, and construction and land development (CLD) loans are widely considered the riskiest sub-category of such bank lending (Balla, Mazur, Prescott, and Walter, 2019). Banks may remain dominant in these loan categories because of their comparative advantage in managing complex lending relationships, such as through monitoring loans.

Even after performing due diligence through underwriting to screen out unacceptable borrowers (adverse selection), lenders must expend resources and monitor the loans to temper borrower incentives to invest sub-optimally (moral hazard). A large theoretical body of literature examining the unique features of banks suggests that a key advantage that banks have over non-banks is the mitigation of this moral hazard problem through their superior monitoring capabilities (Diamond, 1984; Fama, 1985; James, 1987; Diamond and Rajan, 2001; Kashyap, Rajan, and Stein, 2002). Some models suggest that by specializing in certain asset classes, banks have enhanced incentives to monitor (Winton, 1999), and greater levels of monitoring can ultimately lead to improvements in the quality of their loan portfolios (Boot and Thakor, 1997; Winton, 1999). However, because *direct* evidence of monitoring is rarely observed, empirical papers struggle to test many theoretical models of monitoring.

In this paper, we fill this gap in the literature by empirically answering three distinct questions. First, what determines bank monitoring decisions? Second, do banks use the information they collect through

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[1] For example, fintechs and non-bank lenders increasingly originate many types of loans, securitize them, and then sell them to private investors or government entities. Existing studies have established these patterns in mortgage lending (Buchak, Matvos, Piskorski, and Seru, 2018), student loans (Berman and Stivers, 2016), and consumer finance assets, such as automobile loans, credit card receivables, and student loans (Cetorelli, Mandell and Mollineaux, 2012). The two remaining asset classes are commercial and industrial loans and commercial real estate loans, including construction loans (Cetorelli, Mandell and Mollineaux, 2012). See also Fessenden and Muething (2017) for the rising importance of commercial real estate lending for banks.

these monitoring efforts? Third, does bank monitoring affect loan outcomes? Using a proprietary transaction-level dataset of nearly 30,000 construction loans, primarily for residential properties, that spans ten years from a large bank, we construct a novel measure of monitoring: in-person inspections of the construction site by bank-contracted, third-party inspectors ("on-site inspections"). For each construction loan in our sample, we observe the timing and frequency of these inspections, along with the text contained in the inspection reports. The granularity of our data allows us to not only quantify the frequency at which banks obtain information on the project's progress from third parties, but also assess how banks use the information contained within these reports in their decision-making.

We focus on this bank's construction loans because they are uniquely suited for this type of analysis and possess many characteristics which theory predicts would heighten bank incentives to monitor. For example, the bank had a loan portfolio specializing in construction loans where they retained the entirety of the loan exposure. Construction loans are also inherently risky; have an illiquid secondary market; only generate collateral as the project progresses; usually do not generate cash flow; and often lack traditional covenants that can temper monitoring incentives (Winton, 1999; Boot and Thakor, 1997; Rajan and Winton, 1995; Garleanu and Zwiebel, 2009). We also observe contract terms, origination characteristics, and borrower actions throughout the life of the loan, including line drawdowns, payments, and defaults. Thus, this bank's construction lending portfolio provides us with an ideal laboratory to examine the factors contributing to the bank's monitoring efforts, how the bank uses this information in its decision-making post-origination, and how this monitoring ultimately influences loan outcomes.

Banks attempt to mitigate moral hazard problems inherent to lending and control credit risk using monitoring techniques, so the standard monitoring theories mentioned above are broadly applicable. However, within the context of construction loans, moral hazard and loan contracting terms have several idiosyncrasies compared to other types of bank loans. For example, the loan's principal funds the bulk of the collateral's creation. Once the project is completed, the underlying collateral is either sold or rented, and the cash flows generated from that transaction are typically used to repay the loan. Thus, moral hazard generally involves the borrower drawing the loan funds and failing to produce saleable (or

sufficiently valuable) collateral.[2] To alleviate this moral hazard, construction loans are structured with pre-determined draw schedules that mandate that the borrower make adequate progress and allow the bank to assess this progress before the bank will disburse additional funds to continue work on the project. It is common for banks to hire independent, third-party inspectors to conduct on-site inspections at the borrower's expense before approving a draw request, though not all draw requests are accompanied by on-site inspections.

We construct three loan-level measures of monitoring intensity. First, we calculate the natural log of the total number of on-site inspections over the lifetime of the loan. A second measure normalizes the number of on-site inspections by the number of days before the loan reached its terminal state at the bank, which could be maturity, rolling to a permanent loan, prepayment, or default. The third measure is the number of months until the loan's first on-site inspection. When monitoring is beneficial for banks, they may have incentives to acquire information more frequently or initiate inspections earlier. Approximately 96 percent of construction loans in our sample have on-site inspections. The average sample loan has a term of 13.68 months, 12.52 draw attempts, 8.15 on-site inspections, and the initial inspection occurs approximately 3.01 months after the origination date.

Relying on the predictions of several seminal theoretical models, we first examine whether banks substitute monitoring intensity (on-site inspections) with loan origination characteristics, such as price, quantity, and term to maturity. Consistent with the predictions in Diamond (1989, 1991), we find evidence of a negative relationship between on-site inspection intensity and loan spreads and fees at origination, yet a positive relationship between on-site inspection intensity and loan amount. We also find that shorter maturity loans have more frequent on-site inspections. This finding is consistent with Rajan and Winton (1995), Barclay and Smith (1995), and Park (2000), who argue that banks receive more value from monitoring shorter term loans.

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[2] This problem may arise because the borrower or the building contractor simply steal the funds. Alternatively, the problem may manifest if the contractor substitutes lower quality materials or if the borrower misdirects the funds to other projects, which are common issues in construction. For a more detailed discussion of the risks in construction lending, see Johnston Ross, Nichols, and Shibut (2021).

Pennacchi (1988) asserts that the heart of the bank's monitoring function is to limit risk in borrowers' projects and reduce the probability of default, suggesting that banks should be more likely to monitor projects with a greater ex ante probability of default. During the housing boom prior to the financial crisis of 2008, banks implemented lax underwriting standards and granted high risk construction loans to borrowers and projects that were less credit worthy than had historically been the case.[3] The granular nature of our loan documentation allows us to examine the relationship of monitoring with borrower- and project-risk using proxies based on hard underwriting criteria as well as classifications of loans as made by loan officers. We find that loans to borrowers with lower credit scores and higher combined loan to value ratios (CLTV) are monitored more intensely over the course of the loan, suggesting that loans with higher risk borrowers were monitored more. Furthermore, this bank also had a special program marketed to individuals who did not necessarily have any construction experience to build their dream homes. Loans made through this program were also monitored more. Relatedly, loans flagged as "speculative," meaning they were built to be sold later in the general market, rather than to pre-committed buyers, are also monitored more. In sum, these results suggest that while there was a nationwide trend for banks to make higher risk loans during the housing boom, banks would still attempt to manage the loan-level risks associated with these construction projects.

To the best of our knowledge, we are the first paper to examine the effect bank lending relationships have on monitoring. Extant theoretical models assert that banks are special because they are capable of gaining information through lending, which enhances their monitoring ability (Diamond, 1984; James, 1987; Besanko and Kanatas, 1993). If repeated interactions through relationships with borrowers provide the bank with additional information that can be reusable across projects (Boot, 2000), this could lead to a decrease in monitoring. However, to the extent that the bank has additional exposure to the borrower, it may monitor more to manage this concentrated exposure. We create a variable indicating

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[3] Ben S. Bernanke, the former Chairman of the Federal Reserve, said, "Stronger regulation and supervision aimed at problems with underwriting practices and lenders' risk management would have been a more effective and surgical approach to constraining the housing bubble than a general increase in interest rates." (Rampell, Catherine (2010), "Lax Oversight Caused Crisis, Bernanke Says" *The New York Times*, January 4).

whether the borrower has a previous construction loan with the bank and show that bank-borrower relationships are associated with reduced monitoring. One potential interpretation for this finding is that these relationships with borrowers provide value to banks by reducing monitoring costs because the private information that the banks receive from monitoring is reusable and can be transferred between projects, consistent with Boot (2000).

Next, we examine whether banks use the information they acquire through monitoring in their decision-making by linking the content of the on-site inspection reports to bank drawdown decisions. Within a panel setting, we map each loan inspection report to the draw request associated with it. Using the textual sentiments defined by Loughran and McDonald (2011), we examine the length of the inspection reports as well as the ratio of words contained in the reports that are positive or negative. We find that on-site inspection reports that are more negative are associated with more draw denials, and positive words have the opposite effect. Since each loan in our sample has multiple draw requests, we are able to saturate the model with loan-level fixed effects, accounting for time-invariant loan-level characteristics, as well as day fixed effects that account for granular time trends.

After establishing that there is a strong relationship between bank incentives to monitor, their realized monitoring actions, and drawdown decisions, we next demonstrate that these monitoring actions affect loan default and highlight their relative importance in relation to underwriting. A bank will monitor a performing loan to avoid or reduce credit quality deterioration, but it may also monitor loans with the highest probability of default more intensely, since the marginal benefit of each additional inspection may be greatest on the riskiest loans. To alleviate this endogeneity problem, we implement an instrumental variable (IV) framework to estimate the causal effects of monitoring. Within the IV framework, we define an instrument that influences monitoring intensity but should not directly affect loan default, controlling for the range of construction project, borrower, and loan characteristics. We exploit the fact that the draw schedules for loans are set at the time of loan origination, and the draw requests are used by the bank as a trigger for an on-site inspection, to use the number of draws as an exogenous shifter for the number of inspections. We posit and verify that more draws are associated with more inspections; we

also expect that draw schedules are not directly related to loan default conditional on the observables we include as controls, especially since they are determined at origination. Within the IV framework, we establish that the negative relationship between monitoring and loan default becomes even stronger. Consistent with theoretical models, this result indicates that enhanced monitoring ultimately reduces the probability of default and improves loan performance (Boot and Thakor, 1997; Winton, 1999; Acharya, Hasan, and Saunders, 2006).

While time-varying loan-level collateral values are difficult to observe and even difficult to define for projects under construction, in subsequent analysis, we examine whether deteriorations in local economic conditions affect bank monitoring and draw request outcomes. We find that construction loans located in zip codes with growth in housing prices are less likely to be inspected and less likely to have draw requests denied, and those located in areas with higher foreclosure rates are more likely to have draw requests denied. To the extent that improvements in local economic conditions negatively correlate with the risk of borrower nonpayment, this finding is consistent with the theoretical findings in Rajan and Winton (1995).

This study provides at least three distinct contributions to extant literature. First, leaning on an established body of theoretical models, we empirically test the determinants of bank monitoring. To the best of our knowledge, this is the first paper that directly quantifies and examines these theoretical monitoring determinants within a set of loans that are non-syndicated and made to individual borrowers. We are also the first paper to directly quantify the frequency and timing of inspections within these loans. Since this bank served a broad customer base in many markets, we believe that many of the results based on this data set are likely to be broadly representative of how banks choose their monitoring actions for construction loans and potentially other types of consumer non-syndicated loans. Second, we demonstrate that banks use the information gleaned from monitoring activities for real-time decision-making, which provides evidence for the foundational assumption that the information collected through monitoring activities is useful to the bank. Our analysis indicates that the content of inspection reports affects bank credit decisions. Third, using an instrumental variables framework and controlling for

adverse selection through hard underwriting measures, we establish causally that monitoring leads to improvements in loan performance, corroborating the predictions of numerous theoretical models that suggest that monitoring can reduce borrower moral hazard post loan origination.

Finally, this study is the first to examine the determinants of construction loan default within a regression framework. As the result of non-bank lending and asset securitization, bank balance sheets have become increasingly concentrated in only a few loan categories, including construction lending. Construction lending on bank Call Reports totaled $403 billion as of the fourth quarter of 2021 and was one of the primary contributors to bank failures during the financial crisis (Office of Inspector General, FDIC, 2012). Thus, it is important for regulators, academics, and banks to understand what contributes to default within this asset class.

2. Literature and Background

a. Related Literature

An extensive body of theoretical models suggests that there are three primary advantages banks have over non-banks: superior information producing (monitoring) abilities, better lending technologies, and the ability to match up liquidity needs between deposit-taking and loan-making (Diamond and Rajan, 2001; Kashyap, Rajan and Stein, 2002). By assuming that a financial intermediary possesses superior monitoring technology (e.g., Diamond, 1991), several studies show that monitoring can positively affect loan performance (Leland and Pyle 1977; Diamond 1984, Diamond 1991; Kashyap, Tsomocos, and Vardoulakis, 2020). However, empirical researchers have struggled to test directly the three primary assumptions underlying this body of theoretical models: 1) banks actively monitor loans, 2) banks use the information they collect while monitoring to affect business decisions, and 3) monitoring influences loan outcomes. Although banks may monitor borrowers by requesting documents, project updates, or collateral appraisals, or by conducting phone calls or on-site inspections over the course of the loan, these direct monitoring measures are not often observable to empirical researchers using commercially available databases.

Reflecting the difficulty of directly quantifying the frequency or intensity of borrower-lender interactions, most of the empirically oriented literature relies on indirect measures. For example, several studies have proxied for monitoring incentives based on syndicate structure (Lee and Mullineaux, 2004; Sufi, 2007; Beatty, Liao, and Zhang, 2019) or distance between the bank and the borrower (Petersen and Rajan, 2002; Degryse and Ongena, 2005). Other studies attempt to quantify the benefits of unobserved monitoring empirically by examining stock returns (James, 1987; Focarelli, Pozzolo, and Casolaro, 2008; Addoum and Murfin, 2020), loan contract terms (Bharath, Dahiya, Saunders, and Srinivasan, 2009), or debt yields (Datta, Iskandar-Datta, and Patel, 1999). Relatedly, elements of the contracting literature analyze the theoretical and empirical determinants of bank monitoring incentives through covenant design (Aghion and Bolton, 1992; Dewatripont and Tirole, 1994; Rajan and Winton, 1995; Wang and Xia, 2014; Prilmeier, 2017).

Numerous studies examine the causes and effects of covenant enforcement by lenders to public firms. This literature relies on the fact that lenders monitor borrowers to identify cases in which borrowers violate covenants, but it does not directly observe or study the underlying bank monitoring actions over the lifetime of the loan. Numerous papers study the effect of covenant violations on borrower behavior and the terms of credit (Chava and Roberts, 2008; Roberts and Sufi, 2009; Demiroglu and James, 2010; Nini, Smith, and Sufi, 2012). Other recent papers study incentives for lenders to use the information gleaned from unobserved monitoring by analyzing drivers of lender discretion in enforcement conditional on borrowers violating covenants (Acharya, Almeida, Ippolito, and Perez Orive, 2020; Bird, Ertan, Karolyi, and Ruchti, 2022a,b; Chodorow-Reich and Falato, 2022).

Our study most closely relates to a small and incomplete literature that has overcome these data challenges to obtain direct evidence of monitoring. Using a direct measure, Cerqueiro, Ongena, and Roszbach (2016) show the value of collateral is an important determinant of monitoring, as demonstrated by the number of months between instances where the bank reviews borrower documentation, though they do not examine its effect on loan outcomes, such as default. Gustafason, Ivanov, and Meisenzahl (2021) use textual analysis to recover various instances of active monitoring in syndicated loans to

corporate borrowers that are primarily non-investment grade. They highlight the role that covenants and syndicate structures, two determinants of loan monitoring not generally applicable to our study, play in the existence of active bank monitoring. We document that the bank monitoring of our loans is dramatically different from the group of syndicated loans that they study. Whereas nearly all (96 percent) loans in our sample are monitored regularly (an average of 2.31 times per hundred days), they show that only 20 percent of syndicated loans are monitored at any point during their lifetime. Furthermore, theoretical models suggest that the interaction between multiple lenders, such as in syndicates, can have complicated effects on individual lender incentives to mitigate adverse selection and moral hazard problems (Diamond 1984; Ramakrishnan and Thakor 1984; Fama 1985).

To the best of our knowledge, our paper is the first study to directly document the on-site monitoring process for any sample of non-syndicated loans to individual borrowers over the entire duration of the loan's lifetime even in the absence of covenant violations. By focusing on the frequency and timing of bank monitoring, the contents of the on-site inspection reports, and implementing an instrumental variables framework, we meaningfully contribute to the literature by directly speaking to the determinants of monitoring on the intensive margin and showing that banks use the information that they collect monitoring. Furthermore, to the best of our knowledge, we are the first paper to empirically show that bank monitoring has a causal effect on loan performance. Loans within our sample also do not have the type of financial covenants most commonly examined within the literature, since the underlying collateral does not generate income over the life of the construction loans. This allows us to look at the incentives of a single lender with limited recourse to monitor individual borrowers.

Finally, we contribute to the sparse literature on construction lending. Some early industry-based case studies that predate the savings and loan crisis highlight the risks associated with residential and CRE lending and establish their importance to economic growth (Rogers, 1975; Tockarshewsky, 1977; Lusht and Leidenberger, 1979). Other studies document that lending in construction and real estate has been an underlying cause both of many historical financial crises within the U.S. and globally (Reinhart and Rogoff, 2011; Friend, Glenos, and Nichols, 2013; Fenn and Cole, 2008) and of the bank failures

associated with these crises (Balla, Mazur, Prescott, and Walter, 2019). Using a proprietary database

consisting of loan-level loss given default (LGD) for a sample of construction loans, Johnston Ross,

Nichols, and Shibut (2021) examine the impact of certain loan-level, bank-level, or market-level factors,

though they are unable to observe bank monitoring actions or speak to the probability of these loans

defaulting. Furthermore, to the best of our knowledge, we are the first study that speaks to construction

loan probability of default (PD).

b. Institutional Background and Motivation

Construction loans fund the creation of a building, and this building serves simultaneously as the

loan's collateral and the primary source of funds to repay the loan. Although it is possible for a builder to

take on the role of an investor/borrower, the borrower typically hires a third-party builder to complete any

necessary regulatory approvals and then perform the construction tasks.[4] Since collateral behind the loan

is created over the course of the loan, it is common for lenders to require borrowers to provide personal

guarantees for construction loans. These guarantees provide the lender recourse in the event of default if

the value of the land or incomplete project pledged as collateral is insufficient for loan repayment.

Analogous to a single-family mortgage loan, construction loans typically also require borrowers to

contribute equity, such as a parcel of land or cash, at the time of the loan's origination.

Construction loans have relatively short maturities that correspond to the phases of development. In

the case of an office complex, the borrower may obtain a land development loan to build a parking lot and

prepare the land for utility hookups. Subsequently, the borrower may obtain a construction loan to build

the standing components of the complex. These loans are typically structured in tranches, where the next

segment of the committed balance will only be disbursed to the borrower when certain completion

thresholds are met. The construction loan documents provide the pre-determined disbursement schedule

corresponding to the various construction phases. Since construction projects rarely generate cash flows

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[4] When obtaining a construction loan, investors frequently form a project-specific Limited Liability Corporation
(LLC) that acts as the official borrower and place the property into the LLC, though less-sophisticated individual
homeowners may choose not to do so.

to the borrower until construction is complete, the loans are structured such that the borrower does not make payments until maturity. At maturity, the borrower can repay the loan, typically with funds from selling the newly built property, or they can roll the loan into a permanent mortgage, often funded by income from leasing the property. The permanent loan might be issued by the same bank that funded the construction loan, in which case the terms of this permanent loan may have been arranged at the beginning of the project.

There are two categories of default associated with construction loans: maturity defaults and term defaults. Maturity defaults occur when the borrower is unable to pay off the construction loan in full at the end of the term; this typically occurs when borrowers are unable to sell collateral at an adequate price or obtain permanent financing. Lenders typically initiate term defaults during the middle of the term of the loan when they do not believe that the borrower will be able to make payments, possibly due to deteriorating market conditions, lack of project progression, or insufficient anticipated demand. In these scenarios, the lender may call the loan or refuse to allow future disbursements.

In comparison to other types of mortgages, monitoring for construction loans is considerably more labor intensive and costly. Acquiring loan-specific information requires specialized training and regular, on-site visits. Specialized third-party real estate experts conduct the on-site inspections contained within our sample, and bank management must interpret their complex reports. This monitoring can also be costly for borrowers. In addition to the time it takes to interact with inspectors, borrowers typically incur the monetary costs charged by the on-site inspectors.

Monitoring of construction loans is also very important. First, monitoring tempers moral hazard in a complex lending relationship with substantial scope for borrower and builder judgment (and incentive misalignment). For example, borrowers might steal funds or misallocate them to un-approved tasks or projects, or builders might substitute lower quality, cheaper materials to reduce their expenses. The scope for mismanagement is significant, especially as unforeseen construction issues, such as changes to timing, input prices, or market changes, arise. Banks must acquire detailed information about the regulatory approval process, the details of the construction itself, and local market conditions. The lender also

determines any necessary adjustments to the loan. The job of a third-party on-site inspector is to assess the project to determine whether the project is running on time and within budget. The inspector's assessment is a critical input to the bank's decision whether to make the next disbursement of funds according to the pre-arranged draw schedule. The bank's informed decisions regarding further loan disbursements incentivize borrowers to complete projects as promised lest they lose access to the rest of a credit line or future credit.

Second, monitoring limits the bank's exposure to unprofitable projects. The collateral for the loan is created over the course of the loan and is often also the primary source of funds to repay the loan. As a result, the borrower's failure to complete the project can be very costly to the bank. When the project is unlikely to reach satisfactory completion, learning this information through monitoring and initiating a term default promptly allows the bank to limit its losses. For a variety of reasons, incomplete construction projects are highly illiquid and typically sell at a substantial discount; advancing additional funding for such a project will increase losses to the lender. For example, transferring a complex construction project, including plans and permits, to a new owner and contractor is difficult, particularly when some elements of the project (e.g., concrete footers) are no longer visible and defaulting borrowers' incentives are misaligned. Additionally, failing projects are subject to increased risks from moral hazard because borrowers may forgo investments that will primarily benefit debtholders (Myers, 1977). As a result, such projects likely suffer from additional "cut corners" like substandard workmanship or substitutions of lower quality materials. Finally, lender repossession and transfer of a failed project involves a period of time in which a construction site sits vacant. Even completed vacant structures degrade relatively quickly due to such forces as water infiltration, fire, theft, and vandalism.[5] Incomplete structures degrade even faster, as they often lack elements of the outer envelope (e.g., windows, doors, or gutters) that protect against water and theft, finished fire protection systems, etc.

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[5] For example, see Knight, Meribah, and Bridget O'Shea (2011), "Foreclosures Leave Pockets of Neglect and Decay," *The New York Times*, October 27.

3. Data

This paper uses construction loan data from the servicing system of a large bank that failed during the financial crisis primarily due to the performance of its primary source of business: single-family home residential lending. Like many banks during the lead up to the great financial crisis, our sample bank made construction loans all over the country. Approximately 20 percent of sample loans are within 150 miles of the nearest bank branch. Although lending across all business lines slowed close to failure, the bank continued to manage this construction portfolio until the end of its life. After the bank failed, it was placed into receivership, and the FDIC collected its data. The banking data were made available to the authors under certain provisions, such as keeping the identity of the bank and customers confidential. The data consist of approximately ten years of transaction-level data for all construction loans in one of the bank's product lines that targeted mostly smaller builders and homeowners.

We build a daily loan-level dataset using events in the lending system, with multiple updates on some days and no updates on others. At origination, the bank collected the identity of the borrower and contractor, the loan terms, and the loan origination characteristics. Each day, we observe the state of each loan as the bank would have recorded it. For variables that are not updated on a daily basis, we can calculate the loan's balance and carry forward previous states and update them as information changes. For example, although a borrower's credit score may vary over time, the bank only records the borrower's credit score at the time of origination, since this is what the bank analyzed to originate the loan. A unique strength of analyzing a large construction portfolio over the course of ten years is that we can observe repeat interactions between the bank and borrowers. Furthermore, we can control for granular time trends.

We define our variables of interest in Table 1 and present summary statistics in Table 2. The full dataset contains approximately 11.59 million loan-day observations for 28,939 loans for projects located all over the continental United Sates. At origination, the average loan has a principal balance (LOANAMT) of nearly $450,000 and a term to maturity (TERM) of 13.68 months, an interest rate that is 3.69 percentage points over the effective federal funds rate at origination (ORIGSPREAD), and

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origination fees (ORIGFEES) of 0.2 percent of the original loan amount. The value of the loan(s) on the property to the value of the completed project (CLTV) averages 75.36 percent. Figures 2a, 2b, and 2c demonstrate the distribution of the project's CLTV (in percent), original loan amount (in thousands), and loan term (in months), respectively. Over a quarter of our sample loans have loan terms that are exactly 12 months.

The bank also collected information on borrowers. The average loan was given to a borrower with a 712.5 credit score (FICO). We also define several indicator variables that describe the bank's documentation for the borrower or project. This bank had a special program specifically marketed to borrowers who wanted to build their own homes but did not necessarily have construction experience, and 46 percent of loans fell into this category (OWNERBUILDER =1). Some loans in the sample were given to repeat borrowers. Approximately 4 percent of loans in our sample are given to borrowers who had previously been granted a construction loan with the bank (REPEATBORROWER = 1).

Finally, the bank collected several items that are unique to construction projects, as opposed to completed commercial buildings or single-family homes. Residential construction loans can be made with prearranged permanent funding or on a speculative basis, where homes are built to be sold later in the general market. Due to their risky nature, banks typically set a predetermined limit on the number of unsold units to be financed at any time. This policy alleviates moral hazard problems of contractors potentially overextending their capacity. Speculative loans make up 9 percent of our sample (SPECULATING). The bank also required borrowers to record the number of budgeted items of a given project on their application, where more items represented more complex projects. The average project has 58.9 line items (BUDGETITEMS), and the sample standard deviation is 15.1 items.

a. Monitoring Measures

For our sample of construction loans, we observe the timing and frequency at which the bank conducts on-site inspections. Before the bank approves a draw request, the site is often inspected. A third party typically conducts these on the construction site, and the primary purpose of the inspection is to document the project's progress. Inspectors check for accuracy of the draw request, assess the

condition of the job site, and evaluate the project's stage of completion. The inspector delivers a comprehensive report to the lender, sometimes including photographs of the property. Nearly all sample loans have regular on-site inspections, and we construct several variables to measure their frequency. For each loan, we construct an indicator variable INSPECTIONDATE that takes a value of one on the days that on-site inspections occur. As shown by Table 2 Panel A, inspections occurred on approximately 2 percent of sample loan-days.

For each loan in the sample, we count the total number of inspections over the lifetime of the loan, ALLINSPECTIONS, and account for skewness by using the log transformation, LOG(ALLINSPECTIONS), for our primary analysis.[6] We also include a variable equal to the percentage of all days that the loan was active on which an inspection occurred, ALLTOTERMINAL, to capture the frequency of inspections. Finally, we calculate the time from origination until the bank's first inspection on the loan (TIMETOFIRST). Since we calculate each of these variables once per loan, their summary statistics are shown in Table 2 Panel B. The average loan in our sample has 8.15 inspections, and the first inspection occurs 3.01 months after the origination date; on average, inspections occur on 2.31 percent of days on which a loan is active. In Figures 2d and 2e, we show the distributions of inspections and draws over the loans in our sample. Although the shape of the draw and inspection densities appear similar, as previously stated, not all draws are associated with on-site inspections, and there are fewer inspections than draws. In Figure 2f, we plot the density of the time until the first on-site inspection (in months). In Figures 3a and 3b, we show the average number of days between draws and inspections for the full sample of loans. Since these loans can vary significantly by term to maturity and approximately 25 percent of sample loans have a term to maturity of 12 months, we show analogous figures for the subset of loans with 12-month terms to maturity in Figures 3c and 3d.

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[6] A total of 1,109 sample loans have zero inspections, so LOG(ALLINSPECTIONS) is undefined for these loans. An additional 231 sample loans have dates that have unreliable inspection dates. All results are robust to dropping this subset of loans.

4. Empirical Determinants of Monitoring

In our initial analysis, we first examine whether banks trade off monitoring intensity with observable loan characteristics within the following loan-level regression framework shown in Equation 1:

$$Monitoring_l = \gamma_1 Origination_l + \beta X_l + \epsilon_l \tag{1}$$

The dependent variable represents the cross-sectional monitoring measures of interest, which include the logarithm of the total number of on-site inspections (LOG(ALLINSPECTIONS)), the percentage of days on which inspections occur (ALLTOTERMINAL; a measure of monitoring frequency), and the time between loan origination and the first inspection (TIMETOFIRST). To isolate the conditional correlation between monitoring and origination characteristics, we include a variety of fixed effects, X_l, to control for unobservable time and macroeconomic conditions at the time of origination. We control for intertemporal variation in monitoring incentives by including fixed effects for each loan origination day, along with the three-digit zip code[7] associated with the borrower and the three-digit zip code associated with the property addresses to control for localized economic conditions.[8] We report our baseline specifications in Table 3. If the private information collected through monitoring is more valuable to banks, we would expect both a higher number of inspections in total (LOG(INSPECTIONS)) and a higher frequency of inspections (ALLTOTERMINAL), which are reported in Columns 1 and 2, respectively. Under the same motives, banks may also choose to collect this valuable information sooner, as indicated by lower values of TIMETOFIRST in Column 3.

a. Loan Characteristics at Origination

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[7] Three-digit zip codes are geographic areas defined by the first three digits of postal codes (i.e., the union of all zip codes sharing the same first three digits). As such, they are larger areas than those defined by five-digit zip codes.
[8] We are unable to include loan fixed effects in this cross-sectional analysis because loan origination characteristics are fixed at the loan-level and would be subsumed by loan fixed effects. In unreported robustness, we replace the property zip code, borrower zip code, and day fixed effects with a quarter-property zip code fixed effect, and the results are generally unchanged.

The first four rows of Table 3 indicate significant associations between monitoring intensity and the four loan characteristics at loan origination: loan amount, term, spread, and fees. As seen in Table 3 Columns 1 and 2, there is a positive coefficient on LOG(LOANAMT), indicating that larger loans are monitored more overall and with higher frequency. The first two columns also indicate that lower interest rate spreads and lower fees at origination are significantly associated with more monitoring.

We also find that longer term loans are subject to less intense monitoring. The coefficient on TERM in Column 1 of Table 3 is positive, but this likely reflects a mechanical result—loans with longer terms mechanically have a longer time period over which inspections can be conducted. In Column 2 of Table 3, however, the dependent variable is the number of inspections normalized by the number of days the loan is open. The coefficient on TERM is negative, which indicates that longer term loans are subject to less frequent inspections. These results are consistent with theoretical models showing that banks derive more value from monitoring shorter term loans (Rajan and Winton, 1995; Barclay and Smith, 1995; and Park, 2000).

In Table 3 Column 3, we examine the amount of time until the first inspection. If banks find the information gained from monitoring more valuable, they may be more likely to initiate the first on-site inspection sooner. For example, in addition to monitoring a risky project *more frequently*, the bank may initiate site inspections *sooner*. If this conjecture is true, we may expect the signs on the loan origination coefficients in Column 3 to be opposite those in Columns 1 and 2. Although the average loan term in our sample is 13.68 months, the first site inspection occurs 3.01 months after origination on average. Consistent with this conjecture, we find that most types of loan origination characteristics that are associated with more (less) frequent inspections are associated with faster (slower) initial inspections, including loans with longer terms to maturity. The results in Table 3 suggest that banks trade off many types of loan terms with monitoring intensity, including the speed of on-site inspection initiations.

b.   Borrower and Project Risk

When underwriting a loan, banks use all of the information available to them to estimate the risk associated with the borrower and project. Although hard measures of borrower quality such as FICO

score may inform the bank about the credit risk of the borrower at the underwriting stage, the bank also documented a number of soft measures of borrower and project risk. If a bank suspects that a borrower will be unable to pay its debt, it may monitor more intensely in attempt to prevent the loan from defaulting, consistent with Pennacchi (1988). In Table 3, we examine the two primary hard underwriting criteria designed to capture borrower and project risk, borrower FICO scores and loan CLTV.

Within the panel setting displayed in Columns 1 and 2, we first show that borrowers and projects with higher risk characteristics (lower FICO scores and higher CLTV ratings) experience more monitoring. For FICO scores, the results of Column 3 are also consistent with our expectation: riskier loans receive their first inspection sooner.

The bank categorized a subset of loans (9 percent of sample loans) as "speculative," indicating that the homes were built to be sold later in the general market, as opposed to being pre-sold to a specific buyer. As discussed in Section 3, banks often cap the number of speculative construction loans that they originate because of their risky nature. Furthermore, the bank gave 46 percent of loans to borrowers taking part in the special program marketed to owner-builders who may not have much construction experience, which may be another indication of a high-risk loan. We also examine whether banks monitored more complicated projects, as proxied by the number of budget items, more intensely. In Table 3, we find that all three measures of potential risk, as indicated by these soft information measures, correlate with more intense monitoring under all three intensity measures. Speculative loans (SPECULATING) are first inspected sooner than other loans, by an amount equal to 28.10 percent (=0.846/3.01) of the full sample average time to first inspection, and borrowers who participated in the special program to build their own home (OWNERBUILDER) received their first on-site inspection 9.5 percent (=0.286/3.01) sooner than the full sample average. Furthermore, more complicated projects, as indicated by more budget items, are inspected more frequently. These results show that the bank monitored riskier loans more, potentially because the information it was extracting on these loans was valuable and the bank was attempting to prevent loan default.

    c.   Borrower Relationships

In our sample, we see a significant number of borrowers conducting repeat business with the bank. We mark a repeat borrower at the time of the origination of their second loan. Existing theoretical models suggest that the information frictions caused by adverse selection and moral hazard can be mitigated in the presence of a single private lender (Diamond 1984; Ramakrishnan and Thakor 1984; Fama 1985). Boot (2000) shows that these mitigation benefits can be magnified if the information garnered by banks over multiple interactions is costly to produce, proprietary to the lender, and reusable. If repeated interactions through relationships provide the bank with additional reusable information across loans, such as borrower payment history, this could lead to a decrease in monitoring. However, to the extent that the bank has additional exposure to the borrower, the bank may choose to monitor these loans more frequently to manage this concentration risk. We examine the association between borrower relationships and bank monitoring in Table 4, where we continue to control for all loan characteristics from Table 3.

Table 4 Columns 1 and 2 indicate that loans with repeat borrowers have fewer and less frequent inspections. Column 3 shows that banks initiate inspections approximately one week later for repeat borrowers (0.294 months). Together, results suggest a novel dimension surrounding the benefits of borrower relationships: reduced monitoring.

5. Bank Monitoring and Decision-Making

Thus far, our analysis has focused on time-invariant determinants of on-site inspection frequency and the time until the first inspection. A natural question to ask is how banks use the information contained within these on-site inspection reports. As discussed in Section 2b, draw schedules are determined at the time of the loan origination. After assessing whether borrowers have made adequate project progress, banks can approve or deny draw requests. Although draw requests are often associated with on-site inspections, the inspections do not occur for each draw request.

Using the text from the on-site inspection reports, we follow the textual analysis procedure outlined in Loughran and McDonald (2011) to calculate the number of words in these reports that are positive (POSITIVEWORDS) and negative (NEGATIVEWORDS), divided by total comment length in

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characters. We also include the comment length as measured in number of characters contained in each report. Using a panel framework, we match these on-site inspection reports to their associated draw requests. We present our framework in Equation 2.

$$DrawDenied_{dtl} = \gamma_1 TextMeasure_{dtl} + \beta X_t + \zeta Z_l + \epsilon_{dtl} \qquad (2)$$

Within Equation 2, $DrawDenied_{dtl}$ is an indicator variable that takes a value of one if a draw request d made at time t for loan l is denied, and $TextMeasure_{dtl}$ represents the vector of textual sentiment measures computed from the on-site inspection report associated with the draw request. We can match 143,074 inspection reports to draw requests, and 13 percent of the matched draws are denied. We report the results in Table 5 with various combinations of controls and fixed effects. Because each loan has multiple draw requests, we are also able to include loan-level fixed effects (Z_l) in some specifications that absorb all time-invariant loan-level unobservable and observable characteristics, including those analyzed in Tables 3 and 4. Furthermore, since we observe many draws and inspections on a given day across loans, we can control for time trends by adding additional fixed effects accounting for the day of the observation (X_t). Although inspectors are fixed at a loan level, we implement inspector-level fixed effects in place of loan-level fixed effects in Column 3 and combine inspector fixed effects with the Table 3 and 4 characteristics in Column 5. To the extent that inspectors use a time-invariant standard inspection template, the inspector fixed effect will difference out any standard language. Regardless of the fixed effects specification shown in Table 5, the results tell a consistent story. Reports with larger proportions of negative words are associated with a greater likelihood of draw denials, and reports with a larger proportion of positive words are less likely to have draw requests denied. The total length of comments generally has less effect, though some specifications indicate longer comments are associated with more denials. These results suggest that banks are actively using the information contained within these reports to determine whether to approve draw requests.

6. Monitoring and Loan Outcomes

a. Determinants of Loan Default

In this section, we explore the determinants of construction loan default before we attempt to quantify any additional effect monitoring has on loan outcomes. We are the first paper in the literature to conduct such an analysis, primarily due to the lack of data available to other researchers. Using a cross-sectional regression framework, we explore how the loan origination characteristics, borrower and project risk, borrower relationships, and borrower actions affect loan default using the regression framework shown in Equation 3:

$$EVENTUALDEFAULT_l = \gamma_1 Variable_l + \beta X_l + \epsilon_l \tag{3}$$

We present regression results in Table 6, where the outcome variable of interest, EVENTUALDEFAULT, is an indicator variable taking a value of one for loans that end in default. The results presented in Table 6 indicate that loans with longer maturities and greater origination fees are more likely to default, though larger loans are less likely to default. Loans to lower quality borrowers, such as borrowers with lower credit scores, are more likely to default. Riskier projects, including those with higher CLTV ratios and those categorized as speculative are more likely to default, though the coefficient on SPECULATING is not statistically significant. Projects with more budget items are more likely to default. Loans made to owners building their own homes are less likely to default, potentially because owners have the intent to occupy their dream home.

b. Marginal Effect of Monitoring

Since monitoring can be costly for the bank, it will only conduct an on-site inspection when it believes that the benefits of the information acquired through this inspection are greater than the incurred costs. One potential reason monitoring may benefit banks is improving loan outcomes, such as lowering the probability of default (Pennacchi, 1988). Therefore, the marginal effect of additional inspections on

default risk should be negative. However, the bank may choose to monitor loans where the marginal benefit of an inspection reducing the default risk is greatest, which is likely for the loans with the highest risk; this would tend to induce a positive correlation between inspections and default risk. This is similar to the problem of identifying the effect of police on crime rates in Levitt (1997), where it is common to have high crime cities with large police forces. Further, more inspections may result in detection of more problems that would lead to default, much like increased policing may observe more crime that would otherwise go unreported. Therefore, our analysis suffers from a classic endogeneity problem, where banks may conduct property inspections of the loans that are most likely to default, and directly examining the relationship between inspections and default probability will produce biased estimates. If this simultaneity problem is severe enough, it may even result in a positive relationship between inspections and default.

To resolve this problem in an instrumental variable setting, we require an instrument to be correlated with the number of inspections performed, yet it cannot be otherwise correlated with the default probability conditional on our set of controls. Because borrower draw requests prompt the bank to initiate inspections before disbursing funds, draw attempts will be correlated with inspection activity. We observe the individual line drawdown requests that prompt inspections from the bank records.

At the same time, the number of draws themselves should not be directly correlated with loan default conditional on all other observables because they are set ahead of time and cannot be ex post manipulated easily by the bank or borrower. To prevent borrowers from drawing down all available loan funds at once, potentially failing to produce the collateral that the project intended to create, draw schedules for the loans are set at the time of the loan origination. Banks collect information during the underwriting process to determine the loan's draw schedule conditional on the loan characteristics. Since the draw schedule is determined at the loan's origination, the best measures that the bank has for the project's risk is based on the information collected during the underwriting process. Within our regression framework, we control for all available information garnered during the initial underwriting process, accounting for all measures of initial credit quality that might affect the scheduled number of draws. Because individual

draw requests require time-consuming recordkeeping and oversight (such as phone calls), even if they do not involve on-site inspections, they are costly to the bank and to the borrower, and the bank cannot simply set an infinite or arbitrarily large number of draws.

We use a measure of draw attempts, DRAWTOTERMINAL, defined as the percentage of all days that the loan is active on which a draw attempt occurs. This will operate as an exogenous shifter on inspection intensity, with loans with more draws tending to have more inspections. The exclusion restriction is satisfied if the draw attempt frequency does not affect the default rate other than through this inspection channel, conditional on the other controls. Since we control for the broad range of project, borrower, and loan characteristics available to the bank in making the loan and setting its terms, including the draw schedule, the instrument DRAWTOTERMINAL is conditionally exogenous to the risk profile or default rate of the loan. Table 2 shows that when measured on the last day of the loan, on average, 2.31 percent of the days the loan was open had an inspection (ALLTOTERMINAL) and 3.64 percent of the days had a draw attempt (DRAWTOTERMINAL).

We present our analysis in Table 7. Table 7 Column 1 shows the marginal effect of more inspections (ALLTOTERMINAL) on default (EVENTUALDEFAULT) under the IV framework. A one percentage point increase in ALLTOTERMINAL, which can be interpreted as an increase from, say, two to three inspections in a 100-day period, would lower the probability of default by 3.64 percentage points. As the default probability is approximately 5 percent for these loans, this is a meaningful improvement in default probability.

Table 7 Column 2 shows the result of the first stage regression, regressing the inspection measure on the draw measure. The first stage has an F statistic of 11, above the rule of thumb of 10 for a weak instrument, and a positive direction as predicted by the relationship that more draws should lead to more inspections. Column 3 shows the same specification as Column 1 within an OLS framework without correcting for the endogeneity problem. Notably, the economic magnitude of the IV analysis is approximately twice the magnitude of the OLS coefficient (Columns 1 and 3), and these differences are statistically significant at the 1 percent level. This result is consistent with the prediction that OLS will

underestimate the magnitude of the causal effect of inspections due to the bank's likelihood of inspecting most the projects most likely to default. Within the IV (OLS) framework, a one standard deviation increase in inspections (ALLTOTERMINAL) is associated with a decreased probability of default of 5.61 percentage points (2.85 percentage points).[9] Analogously, in the IV framework, a one standard deviation increase in inspections results in a decrease in default risk equal to about one quarter of the standard deviation of the default rate (.22, or 22 percent, being the standard deviation of EVENTUALDEFAULT from Table 2). The reduced form model presented in Column 4 shows that the relationship between greater numbers of draws and default is negative.

7. Additional Analysis

a. Collateral Deteriorations

In this section, we examine whether local economic conditions affect bank monitoring decisions. Over the course of the project, local economic conditions may change. This may affect both the value of the underlying collateral as well as the probability the borrower will default. For example, borrowers may be less likely to walk away from a construction project in an area that is experiencing high levels of price appreciation since the completed project may be more valuable. However, decreasing housing prices and high foreclosure rates may depress the value of the underlying collateral or may make it more likely for borrowers to strategically default on the loan.

We construct two measures of local real estate conditions using data from the Federal Housing Finance Agency (FHFA) and Corelogic. Our first variable, HOUSING PRICE INDEX from FHFA, calculates the annualized growth rate in prices within the five-digit zip code corresponding to the project address. The variable FORECLOSURE RATE from Corelogic measures the foreclosure rate of single-family residences in the zip code, updated monthly. The average loan is in a zip code experiencing an

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[9] The impact in the IV framework of a 5.61 percentage point decline is obtained by multiplying the standard deviation of ALLTOTERMINAL (1.54, see Table 2) by the corresponding coefficient in Table 7 Column 1 (-0.0364). Similarly, the OLS effect of 2.85 is obtained by multiplying 1.54 with the coefficient from Table 7 Column 3 (-0.0185).

annualized increase in housing prices of 8.98 percent and a foreclosure rate of 0.60 percent. First, we use

a framework analogous to that of Equation 2 to examine the effect changes in economic conditions have

on draw outcomes.[10] We then implement a daily panel regression framework to test whether local

economic conditions influence the probability of the bank conducting an on-site inspection in Equation 4:

$$INSPECTIONDATE_{lt} = \gamma_1 REAL\ ESTATE\ CONDITIONS_{lt} + \beta X_t + \zeta Z_l + \epsilon_{lt} \qquad (4)$$

Since this analysis is conducted within a panel of daily observations, we include loan fixed effects that

subsume any of the origination characteristics analyzed in Tables 3 and 4. The presence of the loan fixed

effects allows us essentially to compare the loan to itself during periods of relative economic growth or

contraction. In Table 8, we show that increases in housing prices are associated with a decreased

likelihood of a draw request being denied and the bank conducting an on-site inspection. When

foreclosure rates increase, draw requests are more likely to be denied, though there is no statistically

significant effect on the probability of an on-site inspection. Rajan and Winton (1995) show that

collateral can be an important determinant of monitoring. To the extent that improvements in local

economic conditions negatively correlate with the risk of the underlying collateral, this finding is

consistent with the theoretical findings in Rajan and Winton (1995).

   b.   Monitoring During Bank Distress

   Since we have daily loan-level data spanning approximately ten years, we can examine whether the

bank changed its monitoring efforts as it approached failure.[11] For each loan-day, we calculate whether

the bank denied a draw request (DRAWDENIED) rather than approved it and whether the bank inspected

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[10] The analysis presented in Section 5 links on-site inspection reports to their corresponding subsample of 143,073 draw requests. Our full loan sample contains 355,890 draw requests, and not all of them are associated with on-site inspections or can be directly linked to inspector comments.

[11] According to the FDIC Improvement Act (FDICIA), generally, a receiver or conservator must be appointed or other appropriate action taken within 90 days of a bank becoming critically undercapitalized. For more information on the resolution process, see the FDIC's Resolution Handbook (https://ypfsresourcelibrary.blob.core.windows.net/fcic/YPFS/resolutions-handbook.pdf).

the property (INSPECTIONDATE). We define two indicator variables that take a value of one for time periods when the bank is approaching failure. The first indicator variable, YEARBEFOREFAILURE, is an indicator variable that takes a value of one on loan-days within 365 days of the bank's failure, and STARTOFYEARBEFOREFAILURE is an indicator variable equal to one if the loan-day is within the same calendar year of the bank's failure. We test whether the bank's monitoring efforts changed just prior to failure compared to earlier periods using the panel regression frameworks in Equations 2 and 4 and present the results in Table 9. As previously noted, the presence of the loan fixed effects allows us essentially to compare the loan to itself during periods of relative bank health and bank distress. The results in Table 9 indicate that just prior to failure, the bank is more likely to conduct inspections and more likely to deny draw requests, indicating heightened bank caution close to failure.

c. Collateral and Borrower Capital Injections

In this section, we examine whether collateral affects bank monitoring. For single-family homes and other completed structures, a creditor repossesses the collateral of the underlying home and sells it to collect payment if the borrower defaults. If value of the underlying collateral exceeds the debt that the borrower owes the bank, upon liquidation, the bank is paid in full. However, when faced with a default on a construction project, a bank faces significantly more frictions when trying to liquidate the associated assets, since the bank may only be capable of selling the incompletely assembled hard materials. Conversations with industry professionals specializing in construction loans indicate that unfinished projects are typically sold at a substantial discount.

Although it is difficult to quantify the time-varying value of collateral associated with unfinished construction projects, the bank recorded the anticipated collateral at the completion of the loan. At the time of the loan origination, the borrower and bank work together with an appraiser to produce an estimate of the value of the completed project relative to the loan amount. When pursuing a construction project, both the bank and borrower hope that the project creates value above the value of the loan. At origination, the bank records the anticipated value of this project. This variable is different from the CLTV of the project, which is the value of the loan divided by the expected value of the finished project,

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incorporating both expectations of appreciation and borrower contribution. The loans in our sample have an average anticipated value (VALUEADDRATIO) of 110.9 and a standard deviation of 18.8, indicating that, on average, the bank anticipated that the completed construction project would be worth approximately 110.9 percent of the loan plus posted borrower equity.

The empirical predictions associated with this measure are ambiguous. On one hand, if the value of the finished product associated with a loan is expected to be relatively high, the bank may be less likely to monitor the loan because it is less likely to worry about repayment, which is consistent with the empirical results presented in Cerqueiro, Ongena, and Roszbach (2016). On the other hand, a high valuation may be indicative of naïve optimism or a hot speculative market.

In Table 10, we show that the coefficient on VALUEADDRATIO is positive and significant in Columns 1 and 2, indicating that projects with greater promise experience more and more frequent monitoring, pointing more towards the hot market and speculation motive. In contrast to our expectations discussed with respect to Table 3, a one standard deviation increase in VALUEADDRATIO is also associated with a greater time period until first inspection (Column 3). However, the effect is economically rather small: a one standard deviation increase in VALUEADDRATIO increases TIMETOFIRST by about 3 days (0.00563*18.8=0.106 months).

The bank also recorded a measure of "hard costs" at the termination date of each loan. In the process of completing a project, a borrower deploys some capital to pay contractor wages, which have no liquidation value, or hard costs that have some liquidation values, such as construction materials and fixtures. Hard costs can easily exceed the loan amount if the project goes over budget. The borrower may contribute additional personal funds or attempt to secure outside funding. We define a dummy variable that takes a value of one if at the termination date, hard costs exceed the committed amount (BORROWERINPUT), which occurs for 7 percent of the sample loans. A second continuous variable quantifies the amount of hard costs that exceeds the committed loan amount (BORROWERAMT). To a certain extent, both BORROWERINPUT and BORROWERAMT represent borrower "skin in the game," since they are deploying additional personal funds into the project. The borrower associated with the

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average sample loan had hard costs that exceeded the loan amount by 24.21 percent (BORROWERAMT), and the standard deviation was 139.2 percent, indicating that a number of projects significantly exceeded costs.

The analysis in Table 10 indicates that both measures of borrower "skin in the game" are negatively correlated with on-site inspections. One possible interpretation of this is that banks monitor less when borrowers use additional personal capital (or outside funding) to fund the project because they are more personally invested in the project, potentially reflecting more closely aligned incentives between the bank and borrower. Alternatively, because these cross-sectional regressions only measure conditional correlations, it is possible that the bank's *lax* monitoring caused the project to go over budget.

8. Conclusion

A seminal body of theoretical literature asserts that a key advantage banks have over non-banks is their ability to monitor borrowers (Diamond, 1984; Fama, 1985; James, 1987; Diamond and Rajan, 2001; Kashyap, Rajan, and Stein, 2002). A growing body of theoretical models builds upon these early studies by showing the conditions under which banks have incentives to monitor and whether monitoring improves loan performance. However, primarily due to lack of data available to researchers, empirical scholars have struggled to test these theories.

Our proprietary, granular transaction-level data allows us to fill an important gap in the literature by testing well established theories surrounding the determinants of monitoring, understand how banks use the information garnered when monitoring, and understand the influence monitoring has on loan performance. We use a novel measure of observable monitoring: on-site inspections. To the best of our knowledge, we are the first study to test these theoretical predictions regarding monitoring frequency within a set of loans that are non-syndicated and made to individual borrowers.

Using our measure of on-site inspections, we show that lenders are likely to trade off monitoring with more favorable loan terms. Riskier borrowers and projects, as indicated by both harder and softer information measures, have inspections that are more frequent and initiated sooner. We also show that

bank lending relationships have a negative association with on-site inspections, potentially due to banks transferring information between projects.

Using textual analysis, we show that banks use the information that they acquire from monitoring in real time. On-site inspection reports with a more negative (or less positive) text sentiment are associated with a greater likelihood of borrowers being denied draws.

In subsequent analysis, we provide a comprehensive assessment of the determinants of construction default, the first study of its kind, as a preamble to analyzing the incremental effect of monitoring. After implementing an instrumental variable framework and controlling for relevant determinants, we find that loans with more on-site inspections are less likely to default. This result suggests that, in line with theoretical predictions, monitoring ultimately improves loan outcomes and adds value to banks.

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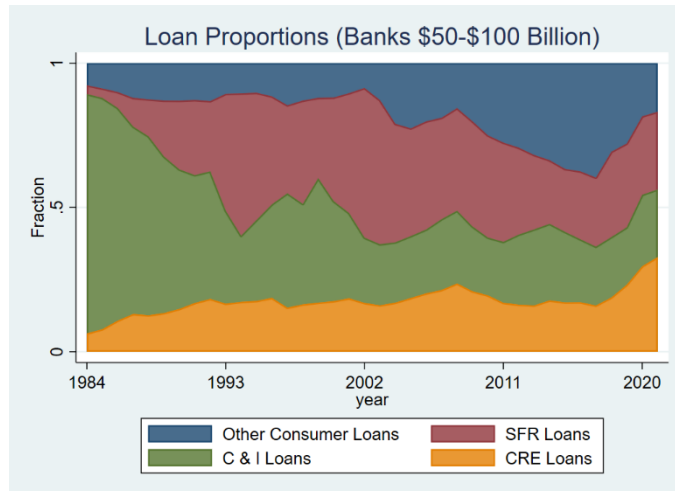
Tables and Figures

Figure 1: Bank Loan Portfolios over Time by Bank Size
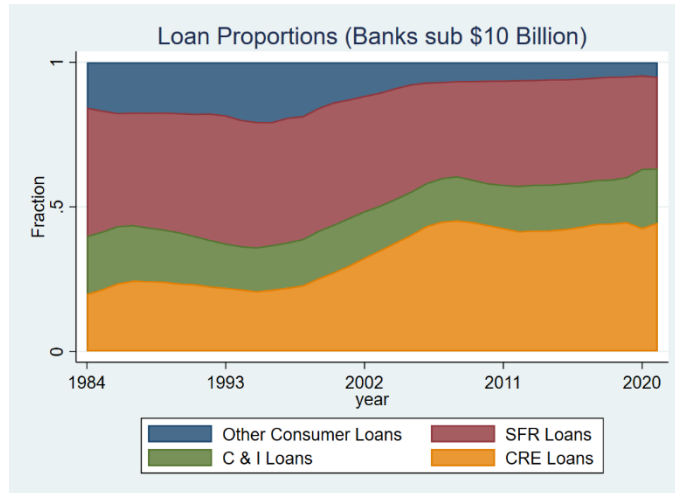
a. Banks with Assets less than $10 billion
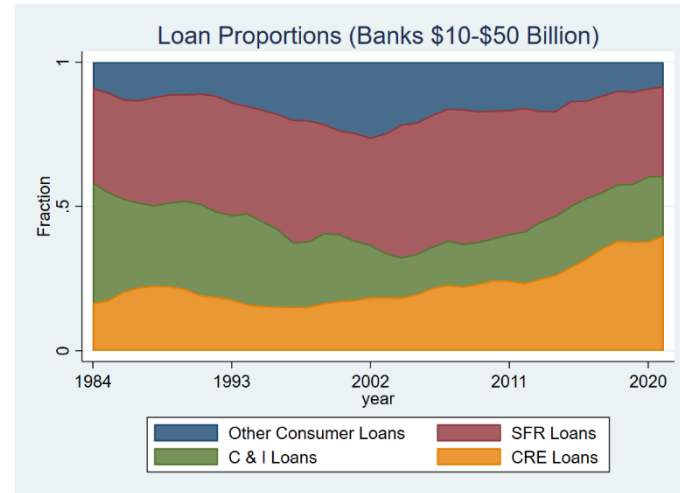
b. Banks with Assets between $10 and $50 billion

c. Banks with Assets between $50 and $100 billion
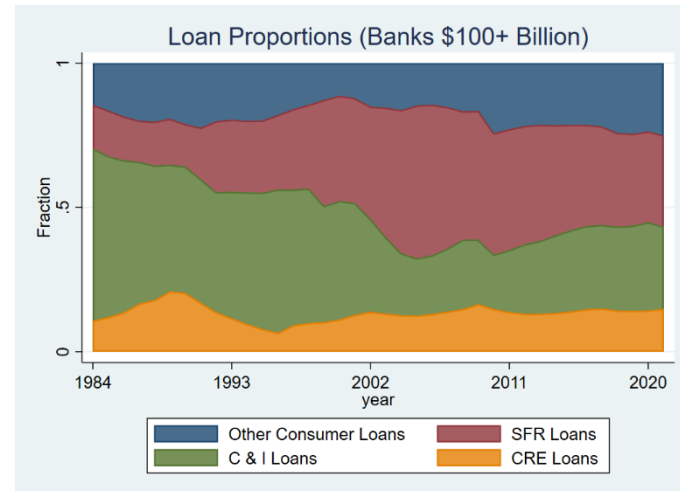
d. Banks with Assets greater than $100 billion

Figure 2: Loan Characteristics
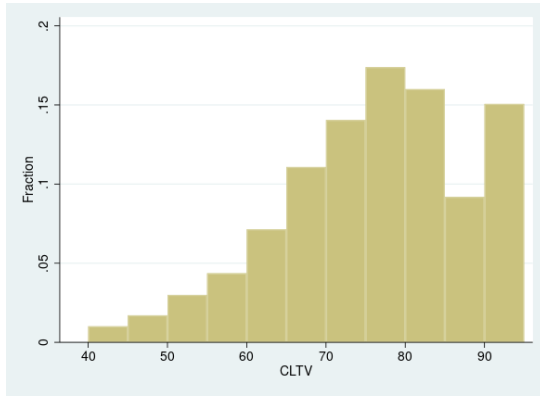
a. Combined Loan to Value of Projects (%)   b. Original Loan Amount of Projects (Thousands)   c. Loan Term (Months)
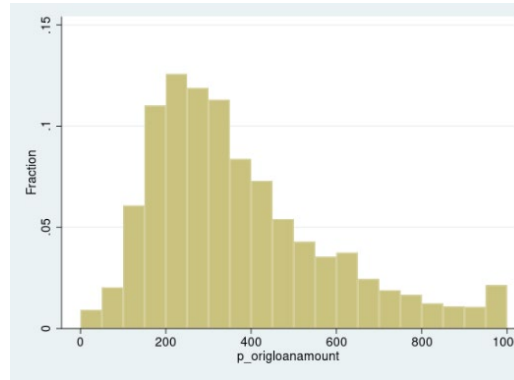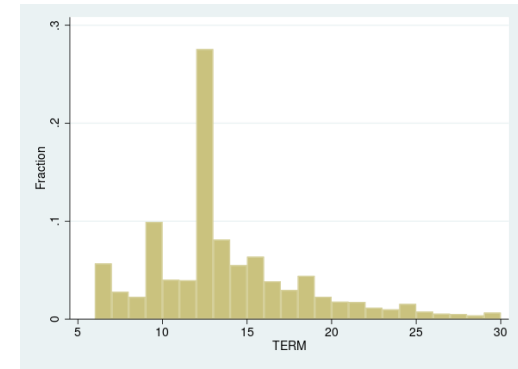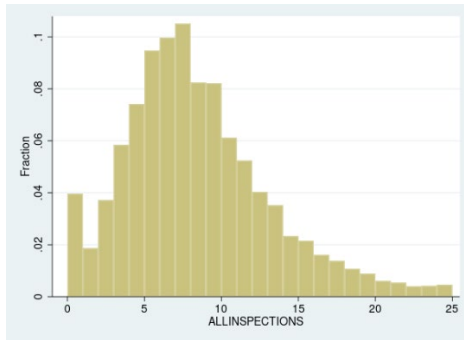
d. Lifetime Inspections of Projects (Count)   e. Lifetime Project Draws (Count)   f. Time to First Inspection (Months)

Figure 3: Average Times to Draws and Inspections

a. Days Between Draws (All loans)

b. Days between Inspections (All loans)

c. Days Between Draws (12 month loans)

d. Days between Inspections (12 month loans)

Table 1: Variable Definitions

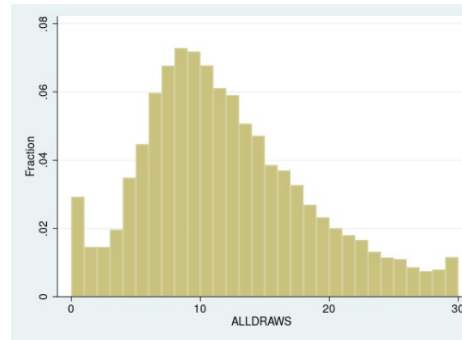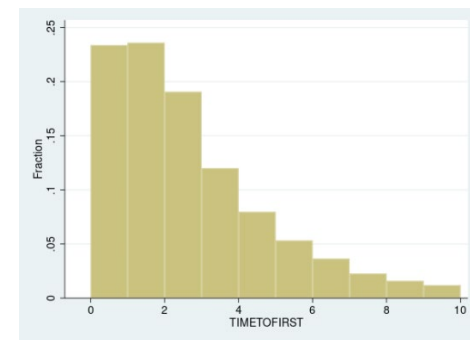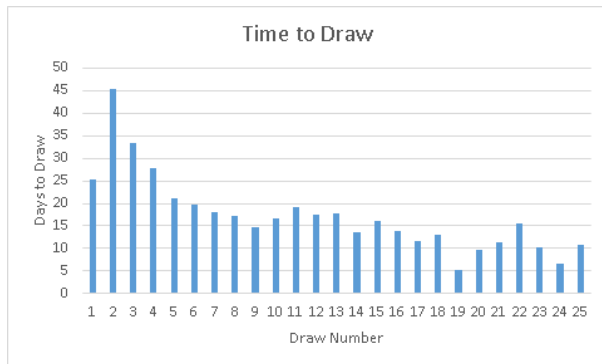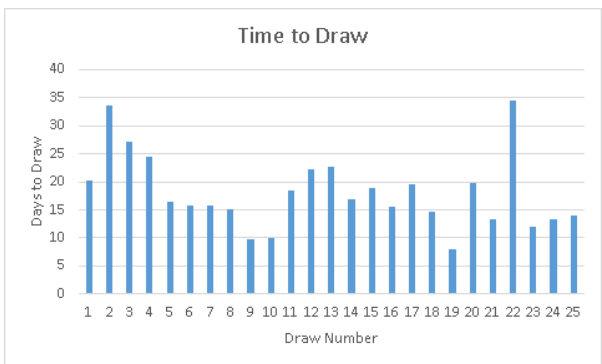| Variable	Definition	Source
ALLDRAWS	is the total amount of draws over the lifetime of the loan.	FDIC
ALLINSPECTIONS	is equal to the number of inspections performed on the loan over its lifetime.	FDIC
ALLTOTERMINAL	is equal to the percentage of all days that the loan is active on which an inspection occurs, capturing the frequency of inspections.	FDIC
BORROWERAMT	is the proportion of expenses in excess of the disbursed amount, with a project 100% over budget having a value of 100. Projects remaining under budget have a value of zero.	FDIC
BORROWERINPUT	is an indicator variable equal to one if the expenses on the project exceeded the disbursed loan amount, thus requiring the borrower to add money, and zero otherwise.	FDIC
BORROWERZIP	is the first three digits of the borrower's zip code.	FDIC
BUDGETITEM	is equal to the count of line items enumerated in the plan for the structure.	FDIC
CLTV	is the value of the loan divided by the expected value of the project expressed as a percent (e.g., 100% CLTV is 100).	FDIC
COMMENTLENGTH	is the length of an inspector's comment in characters.	FDIC
DRAWDENIED	is an indicator variable equal to one if the draw that day is denied and zero otherwise.	FDIC
DRAWSAPPROVEDTODATE	is the total number of draws that are approved over the course of the loan.	FDIC
DRAWSDENIEDTODATE	is the total number of draws that are denied over the course of the loan.	FDIC
DRAWTOTERMINAL	is equal to the percentage of all days that the loan is active on which a draw request occurs.	FDIC
EVENTUALDEFAULT	is an indicator variable that takes a value of one if the loan defaults and is 60 or more days past due.	FDIC
FICO	is the FICO score of the individual borrower from 300 to 850.	FDIC
FORECLOSURE RATE	is the monthly foreclosure rate for all housing. Original data is at the five-digit zip code level, updated monthly.	Corelogic

HARDCOSTS	is equal to the total hard costs spent on the project divided by the total loan amount disbursed by the end of the bank's record of the loan. Thus, 100 would indicate total hard costs are equal to the amount of the loan.	FDIC
HOUSING PRICE INDEX	is equal to the change in housing prices at an annualized rate, for all housing. Original data is at the five-digit zip code level, updated annually.	FHFA
INSPECTIONDATE	is an indicator variable that takes a value of one if an inspection occurred that day and zero otherwise.	FDIC
LOANAMT	is equal to the original loan commitment amount.	FDIC
LOG(ALLINSPECTIONS)	is equal to the natural log of the number of inspections performed on the loan over its lifetime. This variable is not calculated for loans with zero inspections, where the logarithm would be undefined.	FDIC
LOG(LOANAMT)	is equal to the natural log of the original loan commitment amount plus one dollar.	FDIC
NEGATIVEWORDS	is equal to the number of negative words, as defined by the Loughran-McDonald word sentiment dictionary, in a comment divided by its length in characters time 100. Thus, a value of one corresponds to a single negative word in 100 characters.	FDIC
NOTEDATE	is the year the loan note was opened or originated.	FDIC
ORIGFEES	is the total fees paid over the first 30 days of the project divided by the original line commitment.	FDIC
ORIGSPREAD	is the interest rate spread at time of origination of the loan over the federal funds rate.	FDIC
OWNERBUILDER	is an indicator variable that takes a value of one if this is a loan taken by an individual looking to construct a home for them to own and live in, and zero otherwise.	FDIC
POSITIVEWORDS	is equal to the number of positive words, as defined by the Loughran-McDonald word sentiment dictionary, in a comment divided by its length in characters times 100. Thus, a value of one corresponds to a single positive word in 100 characters.	FDIC
PROPERTY ZIP	is the first three digits of the property's zip code.	FDIC
REPEATBORROWER	is an indicator variable that takes a value of one if the borrower has had a loan with the bank before.	FDIC

SPECULATING	is an indicator variable that takes a value of one if the bank indicated the loan was speculative, meaning that the loan was built without a buyer committed to purchase the property upon completion.	FDIC
STARTOFYEARBEFOREFAILURE	is an indicator variable equal to one if the loan-day is within the same calendar year of the bank's failure.	FDIC
TERM	is equal to the contractual term of the loan in months.	FDIC
TIMETOFIRST	is the number of months passing between the opening of the loan and the first inspection. This variable is not calculated for loans which were never inspected and loans where the first inspection is recorded before the loan's origination date.	FDIC
VALUEADDRATIO	is the expected value of the finished project divided by the sum of the borrower equity pledged and loan amount.	FDIC
YEAR	is the year of the loan-day being observed.	FDIC
YEARBEFOREFAILURE	Is an indicator variable equal to one if the loan-day is one year or less before the bank's failure and zero otherwise.	FDIC

Table 2: Summary Statistics

(1)	(2)	(3)	(4)
Variable	N	Mean	SD
Panel A: Loan-Day Variables			
INSPECTIONDATE	11,585,108	0.02	0.14
COMMENTLENGTH	143,074	177.3	196.5
POSITIVEWORDS	143,074	1.40	1.47
NEGATIVEWORDS	143,074	2.33	2.11
DRAWDENIED	355,890	0.12	0.32
HOUSING PRICE INDEX	10,805,736	8.98	11.60
FORECLOSURE RATE	11,537,601	0.60	1.04
YEARBEFOREFAILURE	11,585,108	0.18	0.28
STARTOFYEARBEFOREFAILURE	11,585,108	0.08	0.39
Panel B: Loan-Level Variables			
ALLINSPECTIONS	28,939	8.15	5.17
Log(ALLINSPECTIONS)	27,803	1.97	0.62
ALLTOTERMINAL	28,939	2.31	1.54
TIMETOFIRST	27,567	3.01	2.93
EVENTUALDEFAULT	28,939	0.05	0.22
LOANAMT	28,939	448,303	416,068
LOG(LOANAMT)	28,939	12.76	0.70
ORIGSPREAD	28,939	3.69	1.12
TERM	28,939	13.68	5.62
ORIGFEES	28,939	0.20	0.66
FICO	28,939	712.50	48.62
CLTV	28,939	75.36	13.09
SPECULATING	28,939	0.09	0.28
OWNERBUILDER	28,939	0.46	0.498
BUDGETITEM	28,939	58.90	15.10
VALUEADDRATIO	28,939	110.90	18.80
BORROWERINPUT	28,939	0.07	0.25
BORROWERAMT	28,939	24.21	139.20
HARDCOSTS	28,939	91.55	146.30
REPEATBORROWER	28,939	0.04	0.20
DRAWSDENIEDTODATE	28,939	1.50	1,97
DRAWSAPPROVEDTODATE	28,939	11.03	7.33
ALLDRAWS	28,939	12.52	8.33
DRAWTOTERMINAL	28,939	3.64	2.41

Table 3: Inspections with Loan Origination Characteristics

This table presents the ordinary least squares results where the dependent variables of interest are defined as follows: LOG(ALLINSPECTIONS) is the logarithm of the total number of inspections over the course of the loan, ALLTOTERMINAL is defined as the ratio of total inspections to the number of days between loan origination and the loan's terminal state, and TIMETOFIRST is the number of months until the loan's first on-site inspection date. Table 1 provides further details on variable construction. T-statistics are presented in parentheses, standard errors are clustered at the loan level, and significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1) LOG(ALLINSPECTIONS)	(2) ALLTOTERMINAL	(3) TIMETOFIRST
LOG(LOANAMT)	0.132***	0.242***	-0.508***
	(18.68)	(14.92)	(-15.71)
ORIGSPREAD	-0.0126***	-0.0413***	0.0371*
	(-2.96)	(-4.02)	(1.91)
TERM	0.0182***	-0.0890***	0.278***
	(24.91)	(-50.77)	(83.40)
ORIGFEES	-0.0113*	-0.0261*	-0.187***
	(-1.83)	(-1.81)	(-6.60)
CLTV	0.00251***	0.00419***	0.0162***
	(8.62)	(5.93)	(12.18)
FICO	-0.00163***	-0.00327***	0.00116***
	(-22.27)	(-18.36)	(3.48)
SPECULATING	0.105***	0.344***	-0.846***
	(7.77)	(10.37)	(-13.62)
OWNERBUILDER	0.126***	0.249***	-0.286***
	(16.52)	(13.44)	(-8.20)
BUDGETITEM	0.00615***	0.0158***	-0.000766
	(20.70)	(24.25)	(-0.56)
Property Zip Fixed Effects	YES	YES	YES
Borrower Zip Fixed Effects	YES	YES	YES
Loan Origination Day Fixed Effects	YES	YES	YES
Observations	27,803	28,939	27,567
R-squared	0.352	0.347	0.399

Table 4: Inspections with Relationship Characteristics

This table presents the ordinary least squares results where the dependent variables of interest are defined as follows: LOG(ALLINSPECTIONS) is the logarithm of the total number of inspections over the course of the loan, ALLTOTERMINAL is defined as the ratio of total inspections to the number of days between loan origination and the loan's terminal state, and TIMETOFIRST is the number of months until the loan's first on-site inspection date. Table 1 provides further details on variable construction. T-statistics are presented in parentheses, standard errors are clustered at the loan level, and significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1) Log(ALLINSPECTIONS)	(2) ALLTOTERMINAL	(3) TIMETOFIRST
REPEATBORROWER	-0.0669***	-0.114**	0.294**
	(-3.46)	(-2.45)	(3.32)
Table 3 Controls	YES	YES	YES
Property Zip Fixed Effects	YES	YES	YES
Borrower Zip Fixed Effects	YES	YES	YES
Loan Origination Day Fixed Effects	YES	YES	YES
Observations	27,803	28,939	27,567
R-squared	0.353	0.347	0.399

Table 5: Draw Decisions Based on Inspector Comments

This table presents the ordinary least squares results where the dependent variable of interest, DRAWDENIED, is one if the draw request is denied and zero if it is approved, and independent variables include measures of inspector comments. Table 1 provides further details on variable construction. T-statistics are presented in parentheses, robust standard errors are clustered at the loan-level, and significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1) DRAWDENIED	(2) DRAWDENIED	(3) DRAWDENIED	(4) DRAWDENIED	(5) DRAWDENIED
POSITIVEWORDS	-0.00181**	-0.00206**	-0.00243***	-0.000913	-0.000658
	(-2.15)	(-2.45)	(-2.98)	(-0.76)	(-0.76)
NEGATIVEWORDS	0.00164***	0.00149***	0.00234***	0.00372***	0.00240***
	(2.84)	(2.65)	(4.06)	(5.11)	(4.16)
COMMENTLENGTH	0.00000179	0.00000172	0.0000131*	0.0000185	0.0000177**
	(0.26)	(0.25)	(1.76)	(1.63)	(2.39)
Day Fixed Effects	NO	YES	YES	YES	YES
Loan Fixed Effects	NO	NO	NO	YES	NO
Inspector Fixed Effects	NO	NO	YES	NO	YES
Table 3 and 4 Controls	YES	YES	NO	NO	YES
Observations	143,074	143,074	143,074	143,074	143,074
R-Squared	0.048	0.088	0.048	0.044	0.089

Table 6: Determinants of Default

This table presents the ordinary least squares results where the dependent variable is EVENTUALDEFAULT, which is an indicator variable that takes a value of one for loans that eventually defaulted. Table 1 provides further details on variable construction. T-statistics are presented in parentheses, robust standard errors are clustered at the loan-level, and significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1) EVENTUALDEFAULT
LOG(LOANAMT)	-0.0396***
	(-15.42)
ORIGSPREAD	0.00221
	(1.36)
TERM	0.00626***
	(22.54)
FEES	0.0681***
	(29.93)
CLTV	0.000738***
	(6.60)
FICO	-0.000276***
	(-9.79)
SPECULATING	0.00741
	(1.32)
OWNERBUILDER	-0.0116***
	(-3.94)
BUDGETITEM	0.000423***
	(4.09)
REPEATBORROWER	-0.00462
	(-0.63)
Property Zip Fixed Effects	YES
Borrower Zip Fixed Effects	YES
Loan Origination Day Fixed Effects	YES
Observations	28,939
R-squared	0.251

Table 7: Instruments for Inspections to Predict Default

Column (1) shows the results of the IV estimation second stage, Column (2) the first stage, Column (3) OLS estimation, and Column (4) the reduced form. The dependent variables of interest are EVENTUALDEFAULT, which is an indicator variable that takes a value of one for loans that eventually defaulted, and ALLTOTERMINAL, defined as the ratio of total inspections to the number of days between loan origination and the loan's terminal state. This specification uses the draw schedule, DRAWTOTERMINAL, as an instrument. Table 1 provides further details on variable construction. T-statistics are presented in parentheses, robust standard errors are clustered at the loan-level, and significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Draw Schedule as an Instrument			
	(1)	(2)	(3)	(4)
	IV Second Stage	First Stage	OLS	Reduced Form
	EVENTUALDEFAULT	ALLTOTERMINAL	EVENTUALDEFAULT	EVENTUALDEFAULT
ALLTOTERMINAL	-0.0364***		-0.0185***	
	(-23.36)		(-18.81)	
DRAWTOTERMINAL		0.363***		-0.0132***
		(119.63)		(-22.22)
Table 3 and 4 Controls	YES	YES	YES	YES
Property Zip Fixed Effects	YES	YES	YES	YES
Borrower Zip Fixed Effects	YES	YES	YES	YES
Loan Origination Day Fixed Effects	YES	YES	YES	YES
Observations	28,939	28,939	28,939	28,939
R-squared	0.252	0.581	0.261	0.265

Table 8: Macroeconomic Variables

This table presents the ordinary least squares results where the dependent variables of interest are DRAWDENIED, an indicator variable corresponding to draw requests that is equal to one if the draw request is denied and zero if it is approved, and INSPECTIONDATE, which is equal to one if there is an inspection and zero otherwise. Table 1 provides further details on variable construction. T-statistics are presented in parentheses, robust standard errors are clustered at the loan-level, and significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1) DRAWDENIED	(2) INSPECTIONDATE	(3) DRAWDENIED	(4) INSPECTIONDATE	(5) DRAWDENIED	(6) INSPECTIONDATE
HOUSING PRICE INDEX	-0.00201***	-0.0000258**			-0.00135***	-0.0000302***
	(-12.99)	(-2.42)			(-8.40)	(-2.61)
FORECLOSURE RATE			0.0322***	-0.0000384	0.0336***	-0.0000962
			(11.56)	(-0.44)	(10.62)	(-1.01)
Loan Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	330,594	10,805,736	354,787	11,537,601	330,594	10,805,736
R-Squared	0.001	0.000	0.001	0.000	0.002	0.000

Table 9: Bank Actions over Time

This table presents the ordinary least squares results where the dependent variables of interest are DRAWDENIED, an indicator variable corresponding to draw requests that is equal to one if the draw request is denied and zero if it is approved, and INSPECTIONDATE, which is equal to one if there is an inspection and zero otherwise. Table 1 provides further details on variable construction. T-statistics are presented in parentheses, robust standard errors are clustered at the loan-level, and significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) DRAWDENIED	(2) INSPECTIONDATE	(3) DRAWDENIED	(4) INSPECTIONDATE
YEARBEFOREFAILURE	0.0767***	0.00241***		
	(20.50)	(8.09)		
STARTOFYEARBEFOREFAILURE			0.0920***	0.000803**
			(21.38)	(2.56)
Loan Fixed Effects	YES	YES	YES	YES
Observations	355,890	11,585,108	355,890	11,585,108
R-Squared	0.002	0.000	0.003	0.000

Table 10: Inspections with Borrower Characteristics

This table presents the ordinary least squares results where the dependent variables of interest are defined as follows: LOG(ALLINSPECTIONS) is the logarithm of the total number of inspections over the course of the loan, ALLTOTERMINAL is defined as the ratio of total inspections to the number of days between loan origination and the loan's terminal state, and TIMETOFIRST is the number of months until the loan's first on-site inspection date. Table 1 provides further details on variable construction. T-statistics are presented in parentheses, standard errors are clustered at the loan level, and significance is denoted by * p <0.10, ** p < 0.05, and *** p<0.01.

	(1) LOG(ALLINSPECTIONS)	(2) ALLTOTERMINAL	(3) TIMETOFIRST
VALUEADDRATIO	0.00411***	0.00760***	0.00563***
	(18.48)	(14.29)	(5.31)
BORROWERAMT	-0.00140***	-0.000881***	
	(-14.53)	(-10.37)	
BORROWERINPUT	-0.617***	-1.116***	
	(-33.28)	(-25.82)	
Table 3 Controls	YES	YES	YES
Property Zip Fixed Effects	YES	YES	YES
Borrower Zip Fixed Effects	YES	YES	YES
Loan Origination Day Fixed Effects	YES	YES	YES
Observations	27,803	28,939	27,567
R-squared	0.412	0.394	0.399