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Essays on Banks' Resolutions of Problem Mortgage Loans

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Dedication

To my parents and sister for their unconditional love and support

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Essays on Banks' Resolutions of Problem Mortgage Loans

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This dissertation examines banks' resolution of distressed commercial mortgage loans. Following the introduction in the first chapter, the second chapter reviews the literature on banks' resolutions of distressed loans. In chapter 3, I present a model of banks' resolution decisions under information asymmetry. The model shows that banks prefer to renegotiate instead of foreclosing problem loans when there is a cost associated with revealing the quality of their mortgage portfolios.

The fourth chapter presents empirical findings that are consistent with the model, i.e., that banks' resolution decisions are affected by their concerns of revealing negative information through large foreclosures. I find that larger loans are more likely to be renegotiated than smaller loans and that banks take a shorter amounts of time to renegotiate rather than to foreclose on problem loans. Secondly, the impact of loan size on the propensity to renegotiate is magnified for banks with superior past performance and for banks with lower local mortgage distress. In addition, I find that banks that raised new equity capital exhibit a stronger tendency to renegotiate larger problem loans in the previous year.

In chapter 5, as a falsification test, I compare the bank-held sample with a Commercial Mortgage Backed Securities (CMBS) sample that does not share banks' mimicking motives, because special servicers of problem loans are not the originators of those loans. I find that the results are weaker or not present for CMBS, in contrast to the bank loan sample.

In chapter 6, I study banks' resolution of problem loans while considering their problem loan portfolios. I consider two aspects of banks' problem loan portfolios – their relationships with borrowers and the degree of regional diversification. Empirical results suggest that the sample banks choose to act "tougher", i.e., foreclose more, as they have more loans with a borrower. Finally, the degree of geographical diversification in problem loan portfolios may affect banks' resolution decisions. I find that as banks have geographically concentrated problem loan portfolios, they are more likely to renegotiate larger loans, measured either absolutely or relatively.

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Chapter 1

Introduction

One of the consequences of the dramatic fall in real estate prices since 2007 is a large volume of distressed real estate loans on banks' balance sheets. Faced with a distressed loan, a bank can choose to foreclose on the loan and seize the underlying property, or renegotiate the loan, effectively betting that the value of the loan will recover. One concern that has been raised is that banks may avoid foreclosures whenever possible because they do not want to reveal negative information about the true quality of the loans in their portfolios, i.e., instead they choose to "extend and pretend."

This is an important issue because putting off inevitable foreclosures is likely to result in greater subsequent losses in times when real estate prices keep declining. Yet there is little empirical evidence on how banks resolve their distressed loans.[1] This paper attempts to empirically identify cross-sectional variations in a bias to-

[1] For resolutions of residential mortgages, see Piskorski, Seru, and Vig (2010) and Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2011). For resolutions of commercial mortgages, see Brown, Ciochetti, and Riddiough (2006).

wards renegotiation over foreclosure in resolution decisions. Directly testing whether banks renegotiate when they should foreclose is difficult because we do not observe the consequences of the counterfactual decision. Instead, I attempt to infer a bias towards renegotiation by comparing how distressed loan resolution decisions vary across loans of different sizes. I argue that banks are more reluctant to foreclose large loans that they originated in the past than small loans because outsiders infer more about a bank's upfront screening ability from a decision to foreclose on a large loan. I test this argument using data on the resolution of commercial mortgages.

Consistent with banks renegotiating excessively to avoid a reputational hit, I find that banks are more likely to renegotiate (rather than foreclose) a large distressed loan than a small one, other things being equal. Of course, there could be other factors that are correlated with loan size that cause differences in the resolution decision. To address this possibility, I utilize three additional sources of cross-sectional variation. I find that the size difference is sharper when there is more reputational capital at stake, either because the bank in question had better recent performance or because the loan is in a region with fewer distressed properties. Finally, I conduct a falsification test in which I repeat the analysis using a sample of mortgages in Commercial Mortgage Backed Securities (CMBS). The servicers of CMBS loans are not the originators, so they do not face concerns about inference of upfront screening ability that originating banks face. I find that the results are weaker or not present for CMBS, in contrast to the bank loan sample.

These results suggest distortions that could result in efficiency loss. For example, by delaying the timing of foreclosure decisions, banks may recover less from the properties whose values dropped further. Also, by forestalling foreclosures, banks may be losing potential income from new borrowers that the banks would have otherwise. experienced. Furthermore, these results suggest that requiring banks to hold a larger percentage of the loans that they originate on their balance sheets, which has been proposed as a solution to the moral hazard problem at origination, could cause problems by resulting in less efficient problem loan resolutions.

Whether to foreclose on a loan or to renegotiate is not a simple decision for a bank. If a problem loan's current situation is a temporary condition, so that the loan will become healthy in the near future, it may be optimal for banks to renegotiate such loans by extending the terms of loans or decreasing a portion of payments. However, when it is not likely that the collateral value of the loan will be recovered soon, then banks may ultimately lose value by not foreclosing early. For example, the equity owner of the property may take actions that further impair the property's value (e.g., Melzer (2012)). Also, according to Riddiough and Wyatt (1994), foreclosing loans can prevent other borrowers in the market from strategically defaulting as they perceive the foreclosing banks as "tough" and not so willing to renegotiate. Considering the fact that in the recent crisis, many underwater borrowers considered and ultimately chose strategic default, a speedy foreclosure might have been an optimal decision in many cases.[2]

On the other hand, foreclosures could be a negative signal about a bank's true asset value or quality. This is because a foreclosure can be regarded as a bank

[2]See http://www.nytimes.com/2010/01/24/business/economy/24view.html?_r=0, http://blogs.wsj.com/developments/2010/06/28/how-far-underwater-do-borrowers-sink-before-walking-away/, http://money.cnn.com/2011/06/07/- real_estate/walk_away_mortgage/index.htm.

admitting that the problem loan has no other remedy left and that the loan was in fact a bad one. Therefore, investors will likely interpret foreclosures as a negative signal and update their priors about the bank's loan origination skill and will lower their estimate of the bank's true asset value.

Not all foreclosures have the same amount of negative information about banks' types or true asset quality. One can imagine that banks may use simple heuristics that utilize hard information, such as credit scores, when they originate small loans. In constrast, large loans on banks' balance sheets can be risky for the purpose of diversifying their asset portfolios, so banks may be more careful when originating large loans. Furthermore, as regulatory authorities tend to be more attentive to large loans, banks have many reasons to engage in better due diligence activities for large loans.[3] Therefore, originating large loans may require more time and effort, with banks utilizing both hard and soft information before approving them. Then, small foreclosures may only suggest that the banks' simple heuristics were inaccurate or that they might have been simply unlucky. However, large foreclosures are more likely to be regarded as negative signals, because large foreclosures suggest that even with the presumably higher effort, the respective banks still originated poor quality loans.

If banks hesitate to foreclose large loans because of the negative effect of type revelation, we will see cross-sectional differences in foreclosures and renegotiations

[3] According to the "Commercial Bank Examination Manual" from the federal reserve system, division of banking supervision and regulation, "A thorough review of a bank's commercial loan portfolio is one of the most important elements of a bank examination...Commercial and industrial loans and commercial real estate loans subject to examiner review should include the following: All problem loans...; All large loans, defined as loans or aggregations of loans to the same or related borrowers that exceed a dollar cutoff level established by the examiner-in-charge...; Insider loans..."

across loan sizes. One might suggest a competing explanation that a fixed cost to renegotiate might derive the same findings. This is plausible considering that many banks were swamped with a flood of problem loans and simply did not have enough resources to resolve all at one time. If their resources are limited and there is a fixed cost to renegotiate, the unit cost of renegotiation will decrease with loan size, therefore large loans are chosen to be taken care of first and some small ones might not be renegotiated.

To distinguish between these two explanations, I utilize three additional sources of cross-sectional variation as proxies to indentify the group that is more sensitive to the mimicking motive. The first proxy is an indicator for locations with a low number of troubled properties. If the number of troubled properties differs by region, then this could affect the level of visibility of a foreclosure as a negative signal. For example, if a region has relatively small number of distressed properties, a new foreclosure maybe more easily observed and regarded more seriously. Whereas, in a region with a large number of foreclosures, one more foreclosure may not look so "new" or surprising. Not only may the visibility vary, but also the informational content may be different. If a foreclosure occurs in a region with a large number of foreclosures, then investors may interpret it as a systematic outcome, rather than as a bank-specific outcome and therefore, more informative about the quality of a bank's underwriting process.

The second proxy that I use to identify groups who are more or less sensitive about type revelation is past performance. The first rationale to use past performace as a proxy is because of the amount of information content. A new bad signal may be more surprising if a bank has been previously perceived as a good type. A bad signal from a firm already known to be of a bad type would not convey much surprising information, or result in a drastic update of investors' prior beliefs. This is similar to the "visibility" of a signal.[4] Also, high past performers may have more to lose if they reveal their type, in the sense that they cannot enjoy their previous low cost of capital anymore, losing projects.

I use capital raising activities as the third proxy to identify the group of banks that are more likely to be sensitive about outside investors' evaluation. When firms raise capital, whether it is through new equity or new debt, investors will carefully evaluate the firms' value to calculate the fair price of new shares or new debt that they are going to purchase. Therefore, firms that are looking to raise new capital in the near future will be particularly concerned about how they will be perceived by outside investors. Hence, they would have even stronger incentives to avoid actions that may reveal negative information about their asset values or abilities.

I present a simple model that analyzes the aforementioned considerations, and I find results that are consistent with banks' resolution decisions under the presence of a mimicking motive. Firstly, on average, larger loans tend to be renegotiated. Secondly, a bank takes a shorter amount of time for a renegotiation decision, and lastly, in the group that is more sensitive about type revelation, these effects are magnified.

[4] One might argue that the high past performing group may have more slack in terms of making a mistake, because they have already built a good reputation. Nevertheless, it is not likely to be the case in this setting. The logic may be true if we were still in normal times. A mistake can be regarded as an error term in signals within the same economic regime. However, because now we are in a recession where a mistake is much more informative about the true value of assets than in normal times, the previous reputation that was built in normal times does not help much.

To test these predictions, I use the four sources of cross-sectional variations mentioned above - loan size, distress level of the property's location, prior bank performance, and capital raising activities. The latter three are the second layer of cross-sectional variances, serving as my proxies for the more sensitive group of banks about signaling to outside investors. Also, as a falsification test, I compare the bank-held sample to a sample of loans from Commercial Mortgage Backed Securities (CMBS) that do not share the mimicking motive, because the originators of the loans are no longer the owners of the loans after securitization.

Consistent with the model, I find evidence that banks' concerns over revealing their true types play an important role when they decide how to resolve problem loans. On average, foreclosed loans tend to be smaller than renegotiated loans, and the time spent until the decision of foreclosure is on average longer than the time spent until the renegotiation decision. Furthermore, among banks who have performed better previously, or for loans in regions with relatively low numbers of distressed properties, the size sensitivity to renegotiation is stronger. In addition, I find that prior to raising new equity capital, banks exhibit a stronger tendency to renegotiate larger problem loans. This relation is much weaker for other types of capital raising, suggesting that relatively healthy banks that can afford to raise capital through other types of financing are less concerned about revealing negative information through large foreclosures. This finding is consistent with the hypothesis that banks that are more sensitive to ouside investors' valuations tend to be more hesitant to foreclose on larger problem loans.

As a falsification test, I compare bank-held loans to CMBS loans. While there are several differences due to institutional details, most importantly, special servicers of CMBS loans do not have the sort of mimicking motive that banks face when dealing with problem loans. Consistent with the theory, the empirical findings in the bank-held sample are either noticeably weaker or not present in the CMBS loans sample.

In the last chapter, I study banks' resolution of problem loans while considering their problem loan portfolios. I consider two aspects of banks' problem loan portfolios – their relationships with borrowers and the degree of regional diversification. Banks may be more likely to renegotiate, i.e., take softer resolutions, in order to maintain a good relationship if they have many loans with a borrower. Alternatively, banks may be more likely to foreclose to signal that they are "tough" to prevent potential strategic defaults from the same borrower in the future. Empirical results suggest that the sample banks choose to act "tougher" as they have more loans with a borrower. The results appear to be consistent with what we have observed in the recent financial crisis, as lenders have expressed concerns over underwater borrowers' tendency to default strategically.

Finally, the degree of geographical diversification in problem loan portfolios may also affect banks' resolution decisions. In the literature, studies have documented evidence of negative spillovers of foreclosures on nearby property values. If a bank has a very geographically concentrated loan portfolio, the bank may be concerned about a negative spillover of one foreclosure decision on the other loans in its portfolio. On the other hand, if a bank has a geographically diversified loan portfolio, then one foreclosure decision may not have as severe of a negative impact on other loans because they are located physically far away. I find that as banks have geographically concentrated problem loan portfolios, they are more likely to renegotiate larger loans, both absolutely and relatively.

The decision of whether to renegotiate or foreclose on problem loans is an important issue, more so recently with the increasing number of delinquent loans in residential and commercial real estate markets. Previous papers on the optimal resolution of lenders have tried to solve the problem by concentrating on maximizing asset values, using the borrower's financial health and the loan's economic value.[5] However, a severe crisis could be a "moment of truth," and in the recent crisis, banks have been under pressure to handle many distressed loans and have had concerns of revealing negative information through certain resolutions affecting markets' perception of them. By looking at how problem commercial mortgages were handled in the time period until 2011, this thesis studies how the concerns of revealing types affect banks' resolution decisions, possibly resulting in sub-optimal decisions.[6] Therefore, this thesis' attempt to study the resolution decisions of problem loans in banks' perspective of revealing their types is not only academically meaningful, but also is important in explaining what we have experienced in the recent crisis.

The rest of the thesis is as follows. In the second chapter, I review the literature of banks' resolutions of distressed loans. In chapter three, I present a model of banks' resolution decisions under information asymmetry. Chapter four demon-

[5] See Lawrence and Arshadi (1995) and Brown et al. (2006). Although they consider some of the lender's characteristics in their resolution models, the consideration of asymmetric information is neither a crucial factor in their models nor the focus of their papers.

[6] As noted in Graham et al. (2005), they find that "the majority of managers would avoid initiating a positive NPV project if it meant falling short of the current quarter's consensus earnings."

strates empirical results of banks' resolution decisions under information asymmetry. Chapter five shows the falsification test results with a CMBS sample. Chapter six investigates banks' resolutions on problem loans while considering the aspects of their problem loan portfolios. The conclusion follows.

Chapter 2

Literature Review

This thesis studies banks' resolutions of problem loans while considering three different factors. First, I study how information asymmetry affects resolution decisions. More specifically, I hypothesize that banks that are sensitive about how outside investors might perceive the banks' true quality would be more hesitant to foreclose on large problem loans. Considering the probable higher efforts that banks would incur originating larger loans, foreclosing on larger loans may suggest more about the banks' true asset qualities or true underwriting abilities than smaller loans. Therefore, banks may have incentives to avoid larger foreclosures due to their concerns that they would convey negative information about the quality of other loans in the banks' assets or about the banks' underwriting ability.

Secondly, I study how relationships with borrowers affect banks' resolution decisions. Banks may take "softer" resolutions, i.e., more likely to renegotiate, to keep a good relationship if the banks have many loans with a particular borrower.

Or, banks may take "tougher" resolutions, i.e., more likely to foreclose, to prevent future strategic defaults. In the recent crisis where there existed serious concerns over strategic defaults by underwater borrowers, the second hypothesis seems more relevant to what we have observed.

Lastly, I study how the negative spillovers of foreclosures affect banks' resolutions. Many studies document evidence of foreclosures pushing prices down of nearby properties, and anecdotal evidence show that banks in the recent crisis seem to have a thick shadow inventory of loans that are close to defaults. Therefore, when deciding a resolution on an individual loan, banks are likely to consider the possible effect that a resolution may have on other loans in their problem loan portfolios.

In this chapter, I provide theoretical background for the abovementioned topics by reviewing the related literature.

2.1 Information Asymmetry and Earnings Management

Broadly, this paper is most closely related to the literature of resolution decisions of problem mortgages. Brown et al. (2006) study the resolutions of commercial mortgage loans both theoretically and empirically. Their model predicts that borrowers default in anticipation of restructuring outcome. Also, lenders consider the liquidity in the market importantly when they decide foreclosures or the timing of recapitalizations. They provide empirical evidence supporting their model's predictions. More recently, Piskorski et al. (2010) and Agarwal et al. (2011) study the resolutions of residential mortgage loans focusing on the role of securitization. They find that bank-held loans are significantly less likely to be foreclosed than comparable securitized loans.

The second strand of related literature is about managers' decision making when they are concerned about investors' perception of the managers' ability, such as Scharfstein and Stein (1990) and Prendergast and Stole (1996). In Scharfstein and Stein (1990), managers show herd behaviors in investments when they are concerned about their reputations in the labor market. In Prendergast and Stole (1996), managers tend to exaggerate or become too conservative in order to acquire good reputations as learners.

Also, from the fact that different resolutions can be chosen because of the differential impact they may have on banks' financial statements, this paper is closely related to earnings management literature, as the seminal papers of Stein (1989) and Trueman and Titman (1988). Stein (1989) shows that even with rational investors in the financial markets, managers of firms have incentives to manage their earnings. Trueman and Titman (1988) show that managers have incentives to manage their earnings in order to maintain stable earnings. It is because volatile earnings can be interpreted by investors as indicating high risk, and firms perceived to have high risk would suffer low stock prices. So, either to maximize the level of earnings or to minimize the variance of earnings, managers have incentives to manage their earnings. One could think of such earnings management as a result of informational asymmetry.

Graham, Harvey, and Rajgopal (2005) address the idea that most firms consider earnings as one of the most important measures used by outside investors when they evaluate firms. In their survey study, some of the results are quite surprising. For example, the majority of managers who answered to the survey would choose to forego or delay positive NPV (Net Present Value) projects, if starting those projects would interfere with their earnings management. They also answered that they would book revenues earlier as well as delay projects that would sacrifice the current quarter's earnings, within the extent that they follow the accounting rules. These results could explain the sample banks' behaviors in handling problem loans in this thesis. In other words, some banks may have chosen to renegotiate problem loans in order to reduce realized losses in a quarter, even though foreclosing on the loans would have been an otherwise optimal resolution.

More specifically related to the banking literature, many papers show evidence that banks engage in earnings management through loan loss accounting. Bushman and Williams (2012), Kanagaretnam et al. (2003), and Wahlen (1994) are examples of such studies. In the banks' loan loss accounting rules, there exist room for bank managers to have discretion over when and the size of losses from bad loans that they recognize on their books.

Rajan (1994) theoretically studies why there exist fluctuations in banks' credit policies and provides empirical evidence consistent with his model. The main logic of the paper shares the theme of my story here, in the sense that banks are concerned about their reputation to outside investors who cannot directly watch the banks' asset portfolios, and thus engage in earnings management. Furthermore, poor performance is accepted more easily when it is regarded as the result of a market-wide shock. Therefore, banks pay attention to how or what other banks are doing. This is equivalent to the sample banks' behavior in the thesis in that they try to choose the resolution that "good" banks would have chosen for handling their problem loans. Banks' are concerned how they are perceived to outside investors under information aymmetry, because outside investors cannot directly observe their loan portfolios nor the banks' ability to underwrite good loans.[1]

Also, Docking et al. (1997) document that investors actually react negatively to banks' announcements of loan loss reserves, even more strongly when the announcements are accompanied by decreased earnings. Having a stronger negative reaction when accompanied by decreased earnings may suggest that investors actually update their information about the banks' value from loan loss reserves as well as poor earnings.

In addition, when practitioners evaluate the financial strength of banks, earnings stability is very importantly considered when it comes to rating banks' financial strength among practitioners. For example, in Moody's "Bank Financial Strength Ratings," earnings stability is one of the most important factors. Therefore, we have enough support to believe that maintaining a stable and/or a high earnings may be critical when banks decide resolutions on problem loans, if those decisions affect their earnings.

In this thesis, I look banks resolution decisions as "real" decisions that affect banks' asset values, such as project decisions discussed in Graham et al. (2005). I do not view resolution decisions only as accounting management decisions that

[1] Banks' efforts to not appear too differently from other banks when they show poor performance is similar to firms' behavior in Grenadier et al. (2012) to "blend in with the crowd."

affect what appears on banks' financial statements.

Furthermore, managers' motives to alter foreclosure decisions because they may reveal negative information about banks' value in the present paper is consistent with the literature of discretionary disclosure with possible withholding of negative information. Nagar (1999), Verrecchia (2001), Miller (2002), and Kothari et al. (2009), and Hirshleifer and Teoh (2003) are studying managers' possible withholding of negative information. Milbradt (2012) shows the incentive of delaying reporting losses. More specifically related to the banking industry, Laeven and Mojnoni (2003) document empirical evidence that many banks delay provisioning for bad loans until too late.

2.2 Relationships with Borrowers

Often times, banks have multiple loans with the same borrower. For the benefits of saving monitoring costs to screen borrowers, such relationships can make sense for banks. Similarly, individuals or firms may reduce their borrowing costs by having recurring relationships with the same bank.

Information asymmetry between borrowers and lenders is at the heart of the financial intermediary literature. One of the most important type of financial intermediaries, banks are said to have advantages of having better abilities of collecting and processing information on borrowers and of monitoring borrowers. Furethermore, the cost of information production exhibits decreasing return to scale, because by lending capital to the same borrower, banks can save on the fixed cost of information production.

Petersen and Rajan (1994) provide empirical evidence that having multiple relationships affect the lending practice to borrowers. The effects include both the pricing of lending and the amount of lending. From their sample collected from surveying small firms, they find results showing better pricing for borrowers with "ties" with the same banks. Also, they find stronger results for the borrowers with ties having more available credit.

Bharath et al. (2011) provide more recent empirical evidence that borrowing from the same lender lowers the cost of borrowing. In addition to the better terms of pricing, repeated relationships ease the requirement of collateral. Also, similar to the result of Petersen and Rajan (1994), the authors find that repeated relationships increase the amount of available credit to borrowers.

Would banks be more lenient to borrowers with deeper relationships when they handle problem loans? If we use the analogy of the above-mentioned studies, we may expect banks to be more lenient when they handle problem loans from existing borrowers in order to maintain good relationships. Because banks already know their borrowers and want to have future business with them, banks may choose to take "softer" resolutions, i.e., renegotiations rather than foreclosures.

However, the question here is slightly different from how lenders treat repeated borrowers when lending "new" capital. When lending new capital, banks can save the fixed cost of information production. However, when deciding resolution decisions, the cost of information production has already incurred. Therefore, it may not be enough to conclude and expect banks to be more lenient when handling problem loans from existing borrowers, just to maintain good relationships.

In the recent crisis, academicians and industry professionals have been highly concerned about numerous strategic defaults of "underwater" borrowers. Due to the drastically decreased real estate prices, many borrowers were underwater. In other words, the collateral values were less than the amount of loans that the borrowers owed their banks. Therefore, if the borrowers walk away from their properties, they would be financially better off than actually fully paying back their loans. Many borrowers chose to away from their properties, even if they had enough liquidity to pay back their loans. These decisions are called strategic defaults, because the defaults are not necessarily caused by the shortage of liquidity.

In this particular situation, the reputation of banks among borrowers – whether they are easy or tough negotiators – could be critical, affecting the amount of future strategic defaults. Once banks are perceived as "weak," "too nice," or "easy," borrowers in the market will be more likely to default, expecting their "nice" banks to renegotiate their loan terms. If banks are known to be tough renegotiators, borrowers will be less likely to exercise the defaulting option, because the defaulting option also incurs monetary and non-monetary costs for the borrowers.

Riggiough and Wyatt (2004) examine the reputation concerns of banks as negotiators. To summarize their results, lenders will decide the extent to which they are going to be "tough" by comparing the cost of foreclosing and the benefit of reducing potential future defaults from borrowers. Their paper is the first to consider the reputation of lenders as renegotiators and incorporate the effect as a part of future payout of loans. This reputation concern of lenders among borrowers arguably became tremendously critical in the recent crisis. With numerous underwater borrowers, banks' appearing as "easy" renegotiators could trigger massive amounts of strategic defaults from borrowers in expectation of their banks' writing off their loan amounts.

Therefore, we could derive two opposite hypotheses regarding banks' resolution decisions on problem loans with considering relationships with borrowers. The first hypothesis is that banks will be more lenient, i.e., more likely to renegotiate, to the borrowers with multiple loans to maintain good relationships. The second hypothesis is that banks will be more "tough," i.e., more likely to foreclose for the borrowers with multiple loans to prevent future strategic defaults by building reputations as strict lenders.

2.3 Negative Spillover of Foreclosures

If we are to find the optimal resolution decisions on individual loans by only considering those individual loans' characteristics, we must assume that the decision on one problem loan does not affect the economic value of other loans in the same portfolio. However, as in the case of the recent crisis, banks often have multiple problem mortgages in their loan portfolios, and because of the possibility that others may learn their banks' type as renegotiators, or because of the possible correlation in real estate property values, the economic value of those problem mortgage loans in the same portfolios may have a high level of correlation with each other.

Actually, in the recent crisis, there have been active discussion and concerns in the industry about the shadow inventory in banks' portfolio. The shadow inventory usually refers to loans that have not defaulted yet, but are close to defaults in the future. If foreclosing on a loan is an optimal resolution for recovering the maximum economic value of the loan, but the foreclosure affects negatively other loans in the same portfolio, then in the perspective of the whole portfolio, the foreclosure may not be an optimal decision.

Lee (2008) reviews the literature on the negative spillover effect of foreclosures on nearby properties. Lee suggests three economic reasons why the negative spillover effect exist. The first reason is poor maintenance and possible vandalism. The owners of soon-to-be foreclosed properties are likely to be financially challenged. Therefore, they are not going to be able to keep their properties in a good shape, plus even if they could afford to do so, they would actually lack any incentive to keep them in a good shape. Making matters worse, after the foreclosures, if the properties are empty before they find new owners, possible vandalism may occur, all of which will decrease the value of those properties and nearby neighborhood. Secondly, usually most foreclosured properties are sold discounted more than normal sales. Therefore, those discounted trasaction prices will bring down the benchmark prices for similar nearby properties. Finally, by the most basic principle of price determination, i.e., increased supply of sale properties, will push down property values in the neighborhood. As long as the increased supply does not coincide with increased demand, new foreclosures translate into lower prices.

There have been studies documenting the evidence of the negative spillovers of foreclosures. More recently, Lin et al. (2009), Rogers and Winter (2009), and

Schuetz et al. (2009) empirically show evidence of foreclosures pushing down nearby property values. Their findings suggest that the negative effect decreases with the spatial distance from foreclosures and with time passed after foreclosures. Also, Lin et al. (2009) show that the effect is smaller if the real estate market is in a boom state, suggesting positive demand of properties in the market will weaken the negative spillover of foreclosures.

Chapter 3

Model of Resolution Decisions on Problem Loans

3.1 Background and motivation of the model

I provide a simple model that shows banks' resolution decision making on problem loans when they have the motive of mimicking good type banks. Banks are faced with a problem loan portfolio and they have to make resolution decision on each loan, whether to foreclose or to renegotiate. There are two types of banks, good("G") or bad("B"), and each bank has one large loan and two small loans. Banks have one good small loan and one bad small loan regardless of their types. On the other hand, the quality of a large loan is equivalent to the quality of each bank. Therefore, a good bank has a good large loan and a bad bank has a bad large loan. The optimal resolutions for problem loans are different based on the quality of loans. The first best resolution for good loans is to renegotiate. On the other hand, the first best resolution for bad loans is to foreclose.

There are three different settings in the model. The first case is the benchmark case of symmetric information. Investors can observe banks' portfolios, and thus know their types. So, banks choose the optimal resolution that maximizes their troubled asset value. The second case is under asymmetric information where investors cannot observe banks' portfolios directly, but they can observe the actions of banks. Then, banks choose resolutions considering both maximizing their troubled asset value and type revelation concerns. The third case looks at banks' decision making function, with the consideration of the price impact of resolution, the potential negative spillover on their other loans in their non-problem portfolio. Foreclosing loans not only has negative impact on signaling their type, but also might push down collateral prices of other loans in their portfolio further than otherwise. This negative price impact might be substantial in cases where asset fire sales are severe.[1]

Banks originate commercial mortgages among other loans. Commercial mortgages are the loans whose collateral consists of commercial real estate properties, such as office buildings or retail stores. After the origination, banks hold some of the loans on their balance sheets, and other loans are securitized into CMBS deals. When bank portfolio loans are in trouble, bank managers have to decide which res-

[1]One good example would be the recent crisis where we experienced plummeting real estate prices. The downward trend of real estate prices has lasted for many years, because numerous increases in for-sale properties meant a jump in supply whereas there was no material increase in demand due to the struggling economy. In this situation, a resolution decision on one asset in basket could have a negative externality on other asset in basket, which is equivalent to the magnification effect or multiplication effect.

olution action to take on the problem loans.[2] On the other hand, when CMBS loans are in trouble, because bank managers no longer own them on their balance sheets, special servicers are hired to handle the problem loans on behalf of the CMBS tranche owners. The important difference between banks and special servicers is that the mimicking motive does not apply to special servicers. Special servicers' quality cannot be judged by the qualities of loans that they did not originate. Thus, they can implement the optimal remedy for each loan depending wholly on the loan quality, free from investors' judgement.[3]

Being a good loan originator is important not only because it is the first and foremost important ability in the banking industry, but also it is suggestive of the quality of other assets in the bank's balance sheet. A foreclosure of a problem loan means that the collateral value is now hard to recover relative to the previous higher levels, and/or the economic condition of the borrower has deteriorated so much that (s)he cannot keep making payments anymore. In either case, it suggests that the originator was not successful in implementing recession-proof screening rules when originating the loan, carefully appraising the collateral value, meticulously evaluating the borrower's economic ability, or foreseeing macro-economic changes.

I do not model the underwriting process of banks, but this is what I have in mind. In the origination process, banks use simple heuristics using only hard information to originate small loans, and a complicated function using both hard and

[2]Some banks have servicers in-house, while others outsource the servicing of problem loans. In both cases, we could say banks are in control of the resolution decisions. It is because in either case, banks ultimately affect the resolution decisions directly or indirectly.

[3]Special servicers might have moral hazard issues considering the fact that they hold junior tranches in many cases. The comparison exercise of banks and special servicers is analyzed in the later section.

soft information to originate large loans. Originating a small loan or a big loan has different impacts on a bank's portfolio. A big loan could be more efficient if there are fixed costs of originating loans, but also could be risky, making it hard to diversify banks' loan portfolios. Therefore, banks are more careful when making and keeping larger loans in their balance sheet. Consequently, banks will exert more efforts for originating larger loans, utilizing both hard information and soft information about borrowers and collateral properties.

Hence, it is natural to assume that the negative information from foreclosures vary by the size of the loans. If a large loan is foreclosed, investors will significantly adjust their views regarding banks' originating skills and the quality of their rest of the portfolio. Because if large loans have gone bad, even though the banks carefully processed both hard and soft information, that suggest the banks' ability of gathering and processing those information must have been poor. On the other hand, if a small loan is foreclosed, investors will adjust their views less significantly, because the small foreclosure is more likely to be the result of a simple heuristic being inaccurate, or a simple bad luck.

3.2 Benchmark: Symmetric Information

Banks' Maximization Problem:

Good Bank	Foreclose	Not Foreclose
Large Loan	L(G)	L(G) + δ ($\delta > 0$)
Small Loan 1	S(G)	S(G) + δ ($\delta > 0$)
Small Loan 2	S(B)	0

Bad Bank	Foreclose	Not Foreclose
Large Loan	L(B)	0
Small Loan 1	S(G)	S(G) + δ ($\delta > 0$)
Small Loan 2	S(B)	0

This benchmark case is where there is no mimicking motive. Investors can observe the true type of banks and the true value of their assets. Banks do not have any type revelation concern because there are no informational frictions, and they will choose the option that maximizes the value of their assets. Arising from the different quality of underwriting processes, good banks' large loans are of good quality such that their value is higher when they are not foreclosed. Bad banks' large loans are of bad quality such that the value of them is higher when they are foreclosed. Therefore, good banks will not foreclose their large loans, and bad banks will foreclose their large loans at the current period. For small loans, both good type banks and bad type banks will renegotiate small good loans and foreclose small bad loans. Timely foreclosures of bad quality loans without delay could preserve more value, by recovering the highest collateral value, if prices keep dropping during a recession. On the other hand, if banks choose to wait, then they only lose the economic value of problem loans by recovering lower collateral value which dropped while banks wait.

3.3 Banks with a Mimicking Motive: Asymmetric Information

The difference in this case from the benchmark case is that bad banks now have a mimicking motive. For instance, if the banks are in need of outside financing, outside investors' valuation of the banks becomes crucial. For outside investors, because of informational frictions, it is hard to observe the true value of banks' assets or banks' true type or quality. If a difference in the quality of assets induces different actions, then by observing actions, outside investors infer the true quality of assets. The ability to originate good quality loans is one of the most important qualities that a bank is expected to have.

In this second case, we have additional assumptions.

- Banks are in need of raising capital $y from outside investors.
- Investors do not see banks' true types, but they observe banks' resolution actions.
- If a small loan is foreclosed, investors do not update their prior about the bank's true type.
- If a large loan is foreclosed, investors update their prior about the bank's true type.
- Investors' prior about the fraction of good type banks is α, and $1-\alpha$ for bad type banks.

Banks' Maximization Problem:

Good Bank	Foreclose	Not Foreclose
Large Loan	L(G)	L(G) + δ ($\delta > 0$)
Small Loan 1	S(G)	S(G) + δ ($\delta > 0$)
Small Loan 2	S(B)	0

Bad Bank	Foreclose	Not Foreclose
Large Loan	L(B) - C < 0	0
Small Loan 1	S(G)	S(G) + δ ($\delta > 0$)
Small Loan 2	S(B)	0

If there is a mimicking motive, where bad banks do not want to reveal their true type, then bad banks may deviate from choosing the otherwise optimal resolution. As assumed, foreclosures of small loans are not informative about banks' quality. Thus, both good banks and bad banks will choose to foreclose bad small loans. Nevertheless, foreclosing large loans is a bad signal about a bank's type, because banks spend much more resources and skills originating them. So, by foreclosing large loans, banks may preserve higher economic value of the loans, but they may suffer from the revelation of their true type. Then, when deciding whether to foreclose, bad type banks will compare the benefit of preserving the higher value of the loan and the cost of revealing their true type. When the cost of revealing the true type is higher, then they will not foreclose, but will benefit from the issuance of new equity. As a consequence, when banks have concerns over revealing their types, we will see foreclosures of only small loans or delayed foreclosures ("Extend and pretend") as the result of bad type banks' mimicking actions.

Bad type banks reveal their true type

This is a case where bad type banks choose to reveal their true types because the benefit of mimicking does not exceed the cost of choosing a sub-optimal resolution for bad loans. Bad type choose to foreclose their large loans. Outside investors can distinguish the bad type from the good type, because they pursue different resolution methods. The present value of bad type banks' future firm value is V_B. Then bad type banks have to sell the fraction of X_1 to raise \$$y$.

$$X_1 \cdot V_B = y$$

$$\rightarrow X_1 = \frac{y}{V_B}$$

Hence, the firm(bank) value sold for raising capital:

$$X_1 \cdot V_B = \left(\frac{y}{V_B}\right) \cdot V_B = y \tag{3.1}$$

Bad type banks do not reveal their true type: *Mimicking good type*

This is a case where bad type banks choose to mimic good type banks' actions because the benefit of mimicking exceeds the cost of choosing a sub-optimal resolution for bad loans. Bad type choose to not foreclose their large loans. Outside investors cannot tell bad type banks from good type banks. The present value of bad type banks' future firm value is V_B, and the present value of good type banks' future firm value is V_G. Then, the average valuation of banks is $\alpha \cdot V_G + (1 - \alpha) \cdot V_B$. Then bad type banks have to sell the fraction of X_2 to raise \$y.

$$X_2 \cdot \{\alpha \cdot V_G + (1 - \alpha) \cdot V_B\} = y$$

$$\rightarrow X_2 = y \cdot \left[\frac{1}{\alpha \cdot V_G + (1 - \alpha) \cdot V_B}\right]$$

Hence, the firm (bank) value sold for raising capital:

$$X_2 \cdot V_B = [y \cdot \left[\frac{1}{\alpha \cdot V_G + (1-\alpha) \cdot V_B}\right]] \cdot V_B \tag{3.2}$$

When C > L(B), or when (3.2) - (3.1) > L(B), bad type banks would choose to mimic good type banks.

Re-writing C = (3.2) - (3.1) becomes

$$\begin{aligned} C &= \left(\frac{y}{V_B}\right) \cdot V_B - \left[y \cdot \left[\frac{1}{\alpha \cdot V_G + (1-\alpha) \cdot V_B}\right]\right] \cdot V_B \\ &= y \cdot \left[1 - \frac{V_B}{\{\alpha \cdot V_G + (1-\alpha) \cdot V_B\}}\right] \end{aligned}$$

By differentiating C with variables in the formula, we can derive the following:

- $C_y > 0$, $C_{V_G} > 0$, $C_{V_B} < 0$, $C_\alpha > 0$.

As the demand of banks for new capital is higher, or as the supply of capital in the market is lower, the benefit of not revealing banks' true type is larger. In addition, as outside investors' prior of good(bad) type banks is higher(lower), the benefit is larger. Lastly, as the market's prior about the fraction of good type banks in the market is higher, C is going to be higher and the inequality (C > L(B)) is more likely to hold.

Also, it is natural to assume the following:

- If α is positively correlated with high past performance, then $C_{high-past-performance} > 0$.

For an example of cross-sectional variation that can allow us to identify the group that is more sensitive to type revelation, we can think about groups with different level of past performance. If past performance is good, a bad firm may lose much by revealing the actual type because the firm can no longer enjoy its low cost of capital or projects that it used to have. And, we can modify the model in the given structure as follows. For a high past performance group, investors may give a heavier weight on a good type, thus higher α. That is equivalent to saying that a bad type bank with relatively high past performance can keep enjoying a low cost of capital by not revealing their true type.

Also, we can think about the cross-sectional difference by past performance in the perspective of investors updating their priors about firms' true asset values. Specifically, in an economic downturn, the true asset value means the true ability of firms to survive in crises, the true risk level, or the true quality of assets in place, all of which are not easily observed in normal times. Bad performance in an economic crisis is perceived worse if the firm has been "thought" as a good type. One might argue that high past performance group would have more slack for making one bad realization, because the group has maintained good reputation in the past. Nevertheless, in this setting the arguement does not hold, because we are now in a recession, the good realizations in good economic period is not so much indicative about a firm's true quality. Therefore, downward adjustment of investors' prior is going to be magnified in higher prior group.

3.4 Negative Spillover of Foreclosures

Often times, banks have many loans in their portfolio, and a resolution of one loan can affect not only the respective loan, but also other loans in the banks' same portfolio ("Shadow inventory"). The negative spillover effect will be larger if the bank's collateral properties are located closely. Specifically, like the recent crisis where decreasing real estate values have been the center of the problems, sales of certain properties can affect the value of existing properties negatively. And as a result, the defaults of those properties could be accelerated. When the credit in the market has dried up and the new demand for real estate properties is low, a small increase in the supply of for-sale properties on the market can trigger the prices to go down faster and further, resulting asset fire sales from the magnified price drop. Therefore, even if foreclosing a loan could save more loss, in order to protect other loans' value, banks may choose not to foreclose.

Assume now that:

- Investors can observe banks' true type.
- Bad banks have a "good" portfolio with $N_L$number of large loans, and N_S number of small loans.
- Loans in the good portfolio are not yet in default, but are subject to potential defaults in the near future. If a bank forecloses a loan, then the future price of the same sized loan in the good portfolio will decrease by the fraction of d.

Banks' Maximization Problem:

Bad Bank	Foreclose	Not Foreclose
Large Loan	L(B)+$N_L P_L(1-d)$	$N_L P_L$
Small Loan	S(B)+$N_S P_S(1-d)$	$N_S P_S$

In this case, good type banks' optimal decision is the same as the previous two cases, where they choose to not foreclose any size of loans. Foreclosing decision for good type banks are sub-optimal not just because it fails to maximize the value of the loans, but also because it will negatively affect the value of other loans in the good portfolio. There is no benefit of forelosing whatsoever to good type banks. On the other hand, for bad type banks' bad loans, foreclosing is the value maximizing option just in the perspective of preserving the value of the problem loan. But, now with the negative spillover of foreclosures on other loans in the good portfolio, which are not in default yet, but are sensitive to potential defaults in the near future ("shadow inventory"), the benefit of foreclosure may not be so large, or could be even negative.

When the negative spillover by the price pressure of asset fire sales is substantial, bad type banks will choose to not foreclose. The cost of spillover is going to be higher, with the higher number ($N_{L,}N_S$) of loans that are close to default and subject to the price pressure, and with the higher degree of potential fire sale discount (d).

3.5 Implications and testable hypotheses

We can draw several implications from the model and discussion. Firstly, we can consider foreclosure decisions within bank portfolio loans. The relation between the foreclosure decision and loan size is as follows. Due to the non-linearity of banks' production(originating) function, the effect of negative signaling is higher for larger loans. A large foreclosure is a negative sign, but a small foreclosure is not necessarily a negative sign. Therefore, banks will be more likely to renegotiate larger loans and foreclose small loans.

However, by just looking at the positive relation between renegotiation probability and loan size, we cannot conclude that banks' mimicking behavior is the reason behind it. For example, if banks' resources are limited and the cost of renegotiation is largely fixed, then larger loans would have lower unit cost and will be renegotiated first, while small loans may not be worth renegotating. Or, the renegotiated loans observed in the market could be the results of optimal resolution where renegotiation simply maximizes the expected value of the loan. As the model describes, for diversification purpose, banks will spend more resource and skill to originate large loans. Therefore, ex-ante, larger loans will have higher quality. And if large loans have higher option value even in troubled situations, it may be better to give a second chance to large loans. Hence, it is too early yet to conclude that the tendency to renegotiate larger loans is driven by banks' mimicking strategy.

We need a second source of variation to determine if the differences in loan size and duration by resolution types are not just the results of the two alternative explanations. In the time series, there could be times when the benefit of mimicking, or the negative effect of revealing the true type is specifically larger, for example, when the demand for a new capital increases or the supply of capital becomes scarce. With the given dataset, it is hard to test in the time series. All the resolutions in the data are very concentrated around the recent financial crisis, so there is little time-series variation. And, during the real estate crisis, the credit in the market arguably freezed throughout the period.

In the cross section, the first example of a source of variation could be the level of visibility of a foreclosure. For example, if a region has a relatively small number distressed properties, a new foreclosure maybe more easily observed and regarded more seriously. Whereas, in a region with numerous number of foreclosures, a new foreclosure may not look so surprising.

In addition, a bad signal may be more surprising if a bank has been previously perceived as a good type. A bad signal from a bank previously known as a bad type would not convey much surprising information that would result in drastic update in investors' opinions. In the two groups, the less distressed regions and the past high performance group, the negative effect of revealing true type through foreclosing a large loan is particularly high not only in terms of the visibility, but also in terms of losing the future business opportunity that would have been protected otherwise. In other words, even though a bank loses economic value from unnecessarily renegotiating a bad loan, if the bank benefits more from not losing future business (by not revealing their true type or true value), the bank will choose to renegotiate. And the case is more relevant among the banks that have better set of future business opprotunities by maintaining good reputation previously from a good past performance. If you are not far above the bottom, you cannot fall too hard.

Lastly, the model also shows the difference in the timing of foreclosures between banks and special servicers, with banks showing delayed timing of foreclosures. Because special servicers do not have the concern of revealing types through choosing different resolutions, they can choose resolutions that can maximize the economic value of loans. On the contrary, banks are more likely to have the concern of type revelation, so they might choose resolutions that may not maximize the loan values, for the sake of mimicking a (hypothetical) good type. It is worthwhile to note that we should be careful not to compare one resolution method across the two samples. There are likely to be omitted differences between bank-held loans and CMBS loans, plus CMBS special servicers are hired professionals to mainly deal with problem loans, implying that banks and CMBS special servicers may have different level of resources and menu of resolutions. Therefore, the exercise of comparing bank-held loans and CMBS loans is to compare the size and duration differences between foreclosure and renegotiations within each sample, but not by resolutions.

We can summarize testable hypotheses as follows:

Hypothesis 1: If banks are afraid to reveal their true type, smaller (larger) loans are more likely to be foreclosed (renegotiated).

Hypothesis 2: If banks are afraid to reveal their true type, the time spent until foreclosure decision will be longer than the time spent until renegotiation decision.

Hypothesis 3: If the size sensitivity to renegotiate is due to banks' fear of revealing their true type, then the relation will be stronger among high past-performance group or in the region with less number of distressed properties.

Hypothesis 4: If the size sensitivity to renegotiate is due to banks' fear of revealing their true type, then the relation will be weaker among CMBS loans than among bank-held loans.

Chapter 4

Empirical Study of Resolutions Under Information Asymmetry with Bank-held Loans

4.1 Accounting Rules on Problem Loans

Among several channels through which investors can learn about banks' foreclosures, financial statements are one of the most important. In this section, I address the evidence of managers' accounting discretion in loan loss accounting in general, and the different amount of discretion between foreclosures and renegotiations. As to discretion, I focus on the timing and the amount of loss to recognize. If bank managers' discretion over the timing and the amount of loss to recognize are different across different resolution choices, then there may exist reasons for them to prefer a certain choice over the others.

Firstly, the evidence of managers' discretion in loan loss acounting seems to be abundant. For example, the whole strand of literature about banks' earnings management through loan loss provisioning is the foremost evidence that banks have the discretion over troubled loan resolutions for earnings management. Also, many recent articles explicitly or implicitly suggest why banks might prefer certain resolution methods to others because of the different effects on their balance sheet.

Losses on problem loans are one of the items where managers have an ample discretion over when or how much to recognize. Accounting rules provide guidance as to how lenders should recognize losses on their balance sheet. Nevertheless, determining the timing and the amount of losses is quite subjective. Generally Accepted Accounting Principles (GAAP) only says banks should report losses when the losses are "probable" and "estimable", not being explicit suggesting formal criteria. GAAP just implies that the recognition should be not too soon or not too late. Because of diverse characteristics of loans and economic circumstances, it might be difficult for accounting rules to have explicit criteria. Naturally, there exists room for managers to manage these figures depending on their incentives.

Tirole (2006, pages 299-300) discusses this matter as below:

> *Even without resorting to fraud, managers have substantial discretion in their income and balance-sheet statements. That is, they enjoy flexibility even within the confines of the Generally Accepted Accounting Principles. For example, the choice of reserves or provisions for loan losses is always subjective... More generally, estimating the value of investments that are not marked-to-market involves some discretion. This discretion can be used in particular to make the firm look more profitable than it really is. Of course, an under-provision only shifts loss recognition in time. Later provisions will need to be made when losses are actually realized or become impossible to hide and deny.*

In principle, an ideal accounting scenario is as follows. A loan becomes impaired and it is highly probable that the loss will happen over the current accounting period. Then, the bank estimates the amount of loss and increase the level of loan loss allowance (loan loss reserve), a contra-asset item in balance sheet, and also records a loan loss provision, an expense item in income statement. As the actual loss is realized, the bank takes charge-offs, decreasing the amount of loan loss allowance and loan amount in their balance sheet. The first step of adding appropriate amount of loan loss allowance should be recorded in appropriate time, so that banks will have appropriate amount of cushion in their balance sheet to absorb future losses. Below we have time lines of accounting action for renegotiation and foreclosure in ideal scenario.

$$< Figure1(a) >$$

Default happens at t=0. This can be the first time when a borrower misses payment or 90 days or more delinquent. Then, a loss becomes now probable and estimable that the bank should reflect this event on their financial statements. The red box is the action of realizing losses on their financial statements at t=0. The estimated loss amount should increase the loan loss allowance, a contra-asset item in balance sheet, and the loan loss provision, an expense item in income statement. Consequently, the bank's net amount of loans on the balance sheet will decrease and net income will decrease at t=0. Because the bank has already recognized a probable loss at t=0, when the actual charge-off event happens, it will not experience additional losses. (The green arrows do not affect the net amount of loans or net income.)

Nevertheless, if banks have incentives to postpone loss realization on their books, they are not likely to actively recognize losses (at t=0) before they actually take resolutions (t=1 or 2). If banks have not realized enough losses as problems occurred, regardless of foreclosures or renegotiations, taking on any resolution actions will incur accounting losses (t=1 or 2). However, because of the subjective nature of estimating losses, as long as a problem loan has not been foreclosed, a manager may have flexibility when deciding how to realize losses. Therefore, not taking any action or renegotiating loans could be the results of putting of loss recognition from the ultimate foreclosures. Consequently, between foreclosures and renegotiations, banks are more likely to be faster in initiating renegotiations than foreclosures.

$$< Figure1(b) >$$

4.2 Empirical Strategy

I focus on banks' choices between foreclosures and renegotiations among others. Other types of resolutions are less clear as to whether they are initiated by lenders. On the other hand, foreclosures or renegotiations are likely to have been initiated by lenders. Therefore, in order to focus on banks' (lenders') motives behind choosing a certain resolution, I compare foreclosures and renegotiations.

Directly testing whether banks renegotiate when they should foreclose is difficult because we do not observe the consequences of the counterfactual decision. Instead, I attempt to infer a bias towards renegotiation by comparing how distressed loan resolution decisions vary across loans of different sizes. With problem commercial mortgage data, using binary logit models and competing risks models, I show how banks' decisions between foreclosures and renegotiations differ with loan sizes.

Of course, there could be other factors that are correlated with loan size that cause differences in the resolution decision. In order to distinguish the mimicking hypothesis and competing explanations behind the relation between loan size and the propensity to renegotiate, I use three additional sources of cross-sectional variation to identify groups that are more sensitive about revealing their true types by foreclosing large loans. These three sources of cross-sectional variation are past performance measured by ROA, the distress level in the specific region of the loan, and the frequency of capital raising activities in the next year across different types of capital.

Finally, I conduct a falsification test in which I repeat the analysis using a sample of mortgages in Commercial Mortgage Backed Securities (CMBS). The servicers of CMBS loans are not the originators, so they do not face concerns about inference of upfront screening ability that originating banks face. Therefore, if banks are concerned about the possibility of negative information conveyed through large foreclosures to outside investors and have bias to renegotiate large loans, then we expect to see less size sensitivity in a CMBS sample.

Throughout the tests, I consistently control for loans' economic condition variables that may affect their resolution decisions. And in the sample where I match banks' financial statement data to loan-level data, I also control for banks' characteristics that may affect their resolution decisions.

4.3 Data and Variables

Troubled Commercial Mortgage Loans: Real Capital Analytics

For the empirical analysis, I use two datasets. The first dataset is Troubled Assets Search (TAS) from the private data provider Real Capital Analytics (RCA). Among different datasets that RCA provides, TAS is the data of financially challenged commercial properties. For each troubled property, along with the basic physical characteristics of the property, I have the history of loans associated with the property and the record of past transactions of the loans. Each property can have multiple loans associated across time, and the loans may have different lenders. The lenders are mainly composed of commercial banks or private mortgage lenders.

The data is hand collected at the end of 2011, so it covers financially troubled commercial properties and their historical debt information until the end of year 2011. The collected TAS has total of around 4,800 troubled commercial properties. Commercial properties are multifamily apartment complexes, office buildings, retail stores, hotels, or development sites, and loans associated with such kind of properties are defined as commercial mortgage loans. The approximately 4,800 properties have one or more loans associated with them, hence the dataset is an unbalanced panel of troubled assets, with time varying historical loan transaction information and fixed physical characteristics. The original panel of the data has around 9,000 lenders and 23,590 property-loan (historical transactions/resolutions) observations. Among those 23,590 historical transactions, I screen out transactions that are not particularly associated with resolving troubled situation. The dataset has information on only troubled properties, therefore I do not observe the universe of commercial mortgage loans.

Banks' Financial Condition: Call Report

The second dataset contains commercial banks' financial statement information. From WRDS (Wharton Research Data Services) and FFIEC (Federal Financial Institutions Examination Council) website, I construct commercial banks' financial statements dataset for the period of 2001-2011. The original source of these financial statements data is the banks' "Call Report." For regulatory purpose, commercial banks have to report their quarterly consolidated financial statements. This report includes wide range of variables, some of which are confidential, some of which are not. And the confidentiality changes over time, with the trend that more variables have become non-confidential over time. To maximize the use of public variables, the time series begins in the first quarter of 2001 and ends in the last quarter of 2011. (Many variables became non-confidential beginning in 2001.) Also, most of historical transactions of troubled properties in the TAS dataset happened around the recent crisis, so selecting the time period as such did not result in the loss of many observations.

Matching

For the analysis that utilizes banks' characteristics, I match the bank-held loan sample with banks' financial statement dataset. In TAS dataset, for lenders information, only their names are provided. Considering the fact that it is more costly for banks to originate a loan and manage it if the property is far away, I assumed that for each property, lenders are from the same state. One more condition that I require for matching is for banks from the both sources to exist at the same.[1] So, using the information of name and state of lenders from TAS, I match TAS lenders to commercial banks in Call Reports. Because Call Reports are at the consolidated level, most name-state pair from TAS have only one match from Call Reports. For the name-state pairs that have multiple candidates for matching, if the number of candidates is less than or equal to three, then I pick the physically closest candidate using Google maps.[2] If the number is more than three, then to minimize the use of subjective assumptions, I do not match such pairs.[3] After the matching process, around 460 lenders in TAS are matched with commercial banks' financial statement data and around 1,500 historical transactions are matched with lenders' financial statement information.

Definition of Variables

Key variables used in the empirical tests are defined as follows. "LnLoanSize" is ln(loan size in $millions). "Duration" is the number of months spent since a loan has become delinquent until a resolution action has been taken. "LessDistState" is an indicator variable with value zero if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and one otherwise. "Judicial" is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court.

[1]By using the first time and the last time that each bank has appeared in Call Reports, if the horizon is not overlapping with time stamps from TAS, those banks in Call Reports were not matched.

[2]with the shortest distance between property's city and the candidate commercial bank's city

[3]But such cases were not many, only around 5.

“DistBorrower” is an indicator variable with value 1 if it is specified in the data that the borrower is financially distressed. “LoanAge” is age of a loan measured as the number of months passed since the origination of the loan.

The second set of variables is banks’ balance sheet data for the matched commercial banks. “LnBankSize” is ln(Total Assets in $000). “HighROA” is an indicator variable of value 1 if a bank’s previous quarter’s return on asset (ROA) is above the median, 0 if below median. “LLA” is the ratio of loan loss allowance/total loan. “DEF” is the ratio of problem loan/total loan measured as (delinquent loan + non accruing loan)/total loan. “RED” is the fraction of real estate problem loan in the problem loan measured as (real estate delinquent loan + real estate non accruing loan)/(delinquent loan + non accruing loan) that could address the issue of banks’ shadow inventory.

4.4 Summary Statistics

Table 1 shows loan sizes, duration, and frequency of different resolutions. “Beingserviced” means it is specified in the data that a loan is in the process of resolving the troubled situation, but without an indication of any specific resolution has been taken yet. “Foreclosure” means a problem loan is either foreclosure initiated or completed.[4] I define “renegotiation” as the resolutions of refinancing, forbearance,

[4] For the cases where the data has only the foreclosure completion record, but not the foreclosure initiation record, the “duration” variable is less informative as the time spent until a resolution action is chosen and begun. Therefore, in the tests where I use “duration”, the variable “foreclosure” includes only foreclosure initiated observations. Otherwise, in order to maximally use the information in the data, “foreclosure” includes both initiation and completed observations.

extension, or restructuring.[5]

The first notable fact is the difference in loan sizes between foreclosed and renegotiated observations. Forclosed loans' mean size is \$11.66 million (median value of \$5 million), and renegotiated loans' mean size is \$36.56 million (median value of \$17.9 million). Also, foreclosed loans have the smallest size compared to other resolution groups, whereas renegotiated loans are the largest size group. The difference in size is statistically significant as shown by the t-test.

The second notable fact is the duration of resolutions. Duration is defined as the number of months since a problem loan became delinquent until a resolution is taken, based on the data.[6] We see statistically significant difference between foreclosure duration and renegotiation duration, and lenders seem to initiate renegotiation decisions faster than foreclosure dicisions.

4.5 Identification of More Sensitive Group of Banks to Outside Investors' Evaluation

4.5.1 Less Distressed States

In order to test the relation between resolution methods and size of loans, I first run univariate regressions in Table 2. Using only the loan-level dataset, I can

[5]Figures 2 and 3 show the frequencies of initiations of foreclosures and renegotiations in the bank-held sample and the CMBS sample respectively. It is worthwhile to note that in the bank-held sample, there seems to be a seasonality when banks initiate foreclosures or renegotiations. The seasonality does not appear in the chart of the CMBS sample.

[6]Duration should not be mistaken as the length of the process. How long it takes for lenders to start certain resolution action and how long each resolution process takes may be correlated, but at the current stage, the latter is not studied due to the limitation of the data.

utilize more transaction (resolution) observations than in the later tests where I use loan-bank matched dataset. The model I test in Table 1 is as follows:

$$Dummy(Foreclosed)_i = \alpha + \beta 1 * (LnLoanSize)_i + \varepsilon$$

$$Dummy(Renegotiated)_i = \alpha + \beta 1 * (LnLoanSize)_i + \varepsilon$$

In Table 1, panel A shows the results of linear probability models that regress the choice of foreclosures (renegotiations) on the loan size. As the different signs of LnLoanSize variable indicate, larger loans are more likely to be renegotiated, and smaller loans are more likely to be foreclosed. These findings are consistent with the hypotheses that a large foreclosure is a negative signal about the true value of banks' assets.

In Table 1, panel B and C test the following model:

$$Duration_i = \alpha + \beta 1 * Dummy(Foreclosed/Renegotiated)_i + \varepsilon$$

Panel B and C are the results of OLS tests, whether the duration until lenders take an action varies across different resolution choices. On average, lenders wait longer times to initiate foreclosures, and act faster to initiate renegotiations. According to accounting rules, once a foreclosure is initiated, there is not much room for managers' discretion over the timing or the amount of loss to be realized on the book. So, banks likely act slower for foreclosures in order to postpone the loss recognition. On the other hand, managers have relatively more discretion for renegotiations, there is a smaller incentive for managers to put off renegotiation decisions.

Therefore, as they want to hide any negative information as long as possible, we see the slower speed for foreclosures than renegotiations.

I interpret the result of banks foreclosing smaller loans and renegotiating larger loans as banks' mimicking behavior. But this result is not conclusive, because size could be a proxy for other issues. There are two other alternative explanations that could derive the same results. One is a fixed cost of renegotiation. If banks have a limited resource to handle problem loans and the cost of renegotiating is similar regardless of loans sizes, then they may start restructuring large loans first, simply because it is more beneficial. The second possibility is asset management specifity as discussed in Brown et al. (2006). If for larger loans, the defaulted borrowers are more likely to be better at managing the property than potential new borrowers, banks may be more prone to give them the second chance. Therefore, without carefully controlling for factors that capture those stories, one cannot make a definitive statement about the banks' mimicking motive behind the size difference across different resolutions.

One not only needs to control for loan characteristics that may affect resolution decisions, but also needs second layer of cross-sectional variation that serve as a proxy for banks' mimicking motives. As controls for loan characteristics other than size, I use "Judical," "DistBorrower," and "LoanAge." "Judicial" controls for differences of foreclosure process by state, specifically, in states where foreclosures have to go through courts, there may exist bias towards renegotiations. "DistBorrower" controls for borrowers' financial distress condition. If a borrower is financially distressed, then the loan's current quality is more likely to be lower, which makes a renegotiation less of an option. "LoanAge" captures the amount of seasoning of the loan that the more a loan is aged, the less the actual loan amount that the bank has not received yet.

For a second source of cross-sectional variation, I use the level of regional distress. If a bank is in a region with low number of distressed properties, then a foreclosure may be more noticeable to investors, and the investors may interpret the foreclosure more as the bank specific negative information than as the regional systematic negative outcome. Hence, the bank is going to be more sensitive about possibly revealing negative information through large foreclosures. By using the number of distressed properties in each state, "LessDistState" is an indicator variable with value zero if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and one otherwise.[7]

In Table 3, I test the following model:

$Logit(Renegotiation = 1)_i = \alpha + \beta 1 * (LnLoanSize)_i + \beta 2 * (LessDistState)_i + \beta 3 * (LessDistState * LnLoanSize)_i + Controls_i + \varepsilon$

Table 3 shows the result of a binary logit regression that cross-sectionally tests the renegotiation-size sensitivity across regions with different level of distress, controlling for loan characteristics.[8] I choose foreclosures as a base outcome and have

[7]Those are the states with the most number of troubled transaction observations in the data. There is a fast drop of the observations outside of those 8 states. Some might say it is not normalized by the size of each state. For example, TX may not have been so troubled over all, but has many troubled properties in the area because it is a large state. One rationale to use an absolute number of troubled transaction is that in terms of a bad signal's visibility to investors might be highly correlated with the total number of bad signals within in each area. It is a sensible assumption because in newspapers and broadcastings, the news about foreclosures are in most times presented as total number by states. For robustness check, I also define TX as LessDistState in an unreported result, and the finding is only slightly weaker and still very significant.

[8]The logit model is commonly used in the studies of problem loan resolution. See Brown et al.

the value zero, and renegotiations have the value one. The result is consistent with the hypothesis three, that a big loan is more likely to be renegotiated, more so in the states with low number of troubled properties. The coefficients for other controls show the expected signs. In judicial states, for non-financially distressed borrowers, and for loans with lower age, banks tend to renegotiate rather than foreclose.

Table 4 shows the results of competing risks models that also cross-sectionally test the renegotiation-size sensitivity across regions with different levels of distress. Because a competing risks model is a kind of hazard model, its result has a richer interpretation, providing information not only about probabilities but also about speed. So, we can interpret the result as, "Under the presence of other possible resolution (foreclosures), the speed of being resolved by a renegotiation (mimic) is faster when a loan is big, even more so when they are specifically sensitive about type revelation." The result is qualitatively similar to Table 3 in that a large loan has a higher probability to be resolved by a renegotiation, and even more so in the states with low number of troubled properties.

4.5.2 Better Past Performers

The second proxy that I use to identify groups who are more or less sensitive about type revelation is past performance. The first rationale to use past performace as a proxy is because of the amount of information content. As investors update their priors after observing signals (e.g., large foreclosures), for a previously poorly performing group, investors would not move their priors much. However, for a

(2006) and Lawrence and Arshadi (1995).

previously high performing group, investors would move their priors more than for the former group, because the signal has more "new" information. This is also similar to the "visibility" of a signal.

One might argue that the high past performing group may have more slack in terms of making a mistake, because they have already built a good reputation. Nevertheless, it is not likely to be the case in this setting. The logic maybe true if we are still in normal times. A mistake can be regarded as an error term in signals within the same economic regime. However, because now we are in a recession where a mistake is much more informative about the true value of assets than in normal times, the previous reputation that was built in normal times does not help much.

The second rationale is in terms of what banks have to give up when they reveal their type. If a bank reveal its type, it may now be faced with higher cost of capital or less business opportunities. And as banks have had high performance, they are more likely to have been enjoying a low cost of capital and thus able to fund more projects. In other words, they have more to lose, making large foreclosures more costly. Therefore, the benefit of mimicking will be larger in high past performance group, and they will have a bigger incentive to do so.

In this section, I test the renegotiation-size sensitivity across banks with different levels of past performance as following:

$$Logit(Renegotiation = 1)_i = \alpha + \beta 1 * (LnLoanSize)_i + \beta 2 * (HighROA)_i + \beta 3 * (HighROA * LnLoanSize)_i + Controls_i + \varepsilon$$

Table 5 shows the result of binary logit regressions that cross-sectionally test the renegotiation-size sensitivity across banks with different levels of past performance. From banks' financial data from call reports, now we can control for banks' basic characteristics that may affect their resolution decisions. "LnBankSize" is the natural logarithm of banks' total assets, and controls for differences in resources for handling problem loans. "LLA" is the relative amount of loan reserve normalized by total loan, and controls for how conservative banks have been in terms of realizing loan losses. "DEF" is the ratio of problem loan amount devided by total loan, and controls overall quality of banks' loan portfolio. "RED" is the fraction of real estate problem loan normalized by the total problem loan portfolio, and control for banks' potential concerns over their shadow inventories.

One should note that the size of the matched commercial banks sample is relatively small, and the size difference between foreclosures and renegotiations is not strong on average. It could be due to a small sample bias, or because commercial banks actually engage in mimicking behavior less than other type of lenders. Nevertheless, the size difference is very strongly present among high past performance group.[9] "LnBankSize" has a positive and statistically significant coefficient that suggests larger banks may renegotiate more on average, which makes sense, because

[9]In order to help interpreting test results, I show the results of demeaned Logit models and linear probability models in Table A.1. The tests are centered at the mean value of "LnLoanSize." Demeaned results does not change relations among independent variables and dependent variable, but make interpretations much easier for interaction terms. In Table A.1, for the loans with the average size in the sample, "HighROA" does not appear to be significant in the demeaned linear probability model, which means the previously-better-performed banks do not vary renegotiation propensity for loans with the average size. However, in the demeaned Logit model, the variable appears to be positive and significant. This result suggest that the previously-better-performed banks may have better quality loans that are worth renegotiating.

they may have more resources for renegotiations. Also, it is noteworthy that "RED" has a statistically significant and positive coefficient meaning banks' with heavier real estate loan portfolio tend to renegotiate more. The finding is consistent with the story that banks are worried about negative externality of foreclosures on their shadow inventories.[10]

Table 6 replicates the model in Table 3, but with controls for banks' characteristics that may be related to their resolution choices as above. And the same result still holds that in the state with a low number of troubled properties, banks are more hesitant to foreclose large loans.

4.5.3 Capital Raising Activities

I use capital raising activities as the third proxy to identify the group of banks that are more likely to be sensitive about outside investors' evaluation. When firms raise capital, whether it is through new equity or new debt, investors will carefully evaluate the firms' value to calculate the fair price of new shares or new debt that they are going to purchase.

Therefore, firms that are looking to raise new capital in the near future will be particularly concerned about how they will be perceived by outside investors. They

[10]In order to directly test how the accounring management needs affect banks' resolution decisions, in Table A.2, I look at the renegotiation-size sensitivity in the banks with high LLA (Loan Loss Allowance) levels. The results are the opposite of what is expected. I expect the banks with high LLA levels would appear to have negative renegotiation-size sensitivity. The reason seems to be driven by the nature of LLA term, that banks with more problem loans have higher levels of LLA. Also, due to the lack of within-bank variations in the sample, I cannot test with bank fixed effect. The accounting purpose of choosing renegotiations for larger loans is highly motivated and some evidence of it is presented in the thesis. Nevertheless, the effect does not appear in this particular test.

would like to appear with higher value by having high quality assets and a low level of risk. Hence, they would have even stronger incentives to avoid actions that may reveal negative information about their asset values or abilities.

Different types of capital raising activities may result from different characteristics or different qualities of firms. Or, depending on the credit availability in the financial market at different times, there could be trends or waves of specific types of capital raising. In addition, more specific to banking industry, different types of new capital may affect banks' capital level differently. Then, depending on the level of capital, banks may prefer specific types of new capital to other types.

Although it is not black and white, new equity will tend to increase banks' capital level and new debt will not. In other words, more equity-like capital will increase capital level and more debt-like capital will not. For example, regulators in the late 2000s started to pay attention to "tangible common equity" that does not include preferred equity. So, even among equity capital, there exists rather continuous differences.

For empirical tests, I use SNL Financial's banks' capital offering data (SNL, from here on) to see the relation between banks' caital raising activities and their resolution of problem loans. For banks' resolution of problem commercial mortgage loans, I use the TAS dataset from RCA. The SNL data has information of individual banks' or bank holding companies capital offerings and the detailed information for each events.

By linking next year's capital raising frequency and this year's resolution decisions, I attempt to see whether the different degree of signaling concerns affected their foreclosure or renegotiation decisions. Among different types of capital, I look at common equity, preferred equity, senoir debt, and subsidiary trust preferred. As stated earlier, the four types affect banks' ex-post capital levels differently. The more equity-like capital will increase banks' capital levels more.

It is worthwhile to note that there is another layer of cross-sectional difference in signaling motives among the four different types of capital. For example, the fourth type of capital, subsidiary trust preferred, is a popular way of raising capital among banks, because it increases banks' capital similar to other equity-like capitals do. So, it has the advantage of both constituting regulatory capital and being treated as debt for tax purposes. But, the interesting feature of trust preferred securities is that they can be raised by pools of offerings. These pooled offerings lower the previously high transaction costs, and consequently are a more available means of raising capital for smaller banks.

If we draw our attention back to the signaling motives of issuers (banks), this pooled-offering feature suggests a very interesting implication. The banks in pools are not evaluated directly by outside investors anymore. Although a pool of issuers (banks) are rated by credit rating agencies, once they are included in the pool, they become one step away from the direct eyes of outside investors. Therefore, we can carefully hypothesize the banks raised subsidiary trust preferred capital to be less concerned about conveying negative information through large foreclosures before their capital raising activities in the near future.

Table 7 shows the relation between banks' capital raising activities and resolution decisions. "FreqCapRaising" has value of one if banks raised a certain type of capital more frequently than the median frequency in the next year. The medians in the matched sample for common equity, preferred equity, senior debt, and subsidiary trust preferred are 2, 1, 104, and 2, respectively. The coefficient of the interaction term of "FreqCapRaising" and "LnLoanSize" is positive and significant for common equity, not significant for preferred equity and senior debt, and negative and significant for subsidiary trust preferred. The main result is the positive difference between common equity and subsidiary trust preferred, which suggests that banks' signaling concerns lead them to avoid large foreclosures before the near future capital raising activities. The positive differences between common equity and preferred equity, and between common equity and senior debt, suggest similar implications.[11]

[11] In the tests of capital raising activities and resolution decisions, I only use initiations of foreclosures or renegotiations. For the observations that I only see the kind of resolutions, but not the initiation timing, it is not clear when banks started those processes. Therefore, for those cases, it is hard to link or justify the effect of capital raising needs on the previous year's resolution decisions.

Chapter 5

Falsification Tests in a CMBS Sample

5.1 Data

The dataset that is additionally used in this section is also from Real Capital Analytics' TAS (Troubled Asset Search), but is the sample of loans that were securitized into CMBS (Commercial Mortgage Backed Securities) deals. It contains financially distressed commercial properties' physical characteristics and their mortgage loans' historical transaction information up until the end of year 2011. Although there are small differences between the bank-held sample and the CMBS sample in terms of the set of variables, the fact that the two samples share a common data source enables a sensible comparative analysis.

I focus on the difference in resolving behaviors of banks and special servicers as groups with or without the mimicking motive. Special servicers are professionals who are hired to service problem loans in CMBS (Commercial Mortgage Backed Securities). Because they are not the originators of the problem loans, they do not share banks' concerns of revealing their types through resolutions. Therefore, they could be regarded as a benchmark case in the model where there is no mimicking motive.[1] In this exercise, I do not have or utilize special servicers' information other than their names. This is because their financial information is not observable unless the entity is publicly traded.

Because of differences in institutional details and resources for handling problem loans, banks and special servicers may show differences in the proportion of resolutions, i.e., different intercepts. Nevertheless, I am interested in the size sensitivity toward a certain resolution, i.e., different slopes. Therefore, I focus on the coefficients of the two cross-sectional variations, loan size and the interaction of loan size and regional distress level.

[1]Nevertheless, they may suffer the equity holders' asset substitution problem, which could affect their servicing behaviors. In most cases, special servicers are -required to be- junior tranche holders, in an effort to align special servicers' incentives with CMBS investors' (tranche holders') incentives. Also, in most cases, junior tranche holders have a right to fire special servicers if they are not satisfied with the special services' decisions. Nevertheless, because of the structure of CMBS deals, in which foreclosures of loans mean loss realization of junior tranche holders first, special servicers (junior holders) may prefer not to foreclose on the problem loans, which could be a sub-optimal resolution. This problem is called the equity holders' asset substitution problem. If it were not for this equity holders' problem, special servicers would be the benchmark case of optimal resolution decisions, because not being the originators of the problem loans, they are free from the signaling concern of an originator.

5.2 Summary Statistics

Table 9 is summary table for the CMBS sample. We can see that the distributions of each resolution type are slightly different from bank-held sample. We see more fraction of renegotiations, which is sensible considering the fact that they are hired professionals for mainly dealing/servicing problem loans in CMBS deals. They likely have more resources than banks for handling problem loans.[2]

Again, as mentioned above, the fraction (intercept) for each resolution type in each sample does not necessarily represent the story of type revelation concern. Rather, what we are interested in is the size difference and duration difference across resolutions within each sample (slope). Interestingly in the CMBS sample, we do not observe the bank-held sample's stylized facts about differences in size and duration between foreclosures and renegotiations. Foreclosed loans are smaller than renegotiated loans, but the difference is smaller than the bank-held sample and foreclosed loans are not the smallest sized resolution group in the CMBS sample. Also, the duration of foreclosure decision is shorter than renegotiation decisions, which is the opposite of the bank-held case. Table 10 shows the similar findings as in Table 9, but in univariate tests.

5.3 Less Distressed States

In this section, I test the relation between renegotiation-size sensitivity and regional distress levels as following:

[2] Also, they may have different set of resolution options because of the institutional feature that only securitized loans may have.

$$Logit(Renegotiation = 1)_i = \alpha + \beta 1 * (LnLoanSize)_i + \beta 2 * (LessDistState)_i + \beta 3 * (LessDistState * LnLoanSize)_i + Controls_i + \varepsilon$$

Tables 11 and 12 replicate the tests in Tables 3 and 4 with the CMBS sample. The coefficient of "LnLoanSize" is positive and statistically significant. But, as discussed, the univariate relation of loan size may be driven by several things, not only by the negative externality (cost) of type revelation through foreclosures, but also by fixed cost of renegotiation or by different asset specifity. Therefore, this result is expected.

More importantly, in order to test the main hypothesis more clearly distinguishing from alternative explanations, I utilize the second sources of cross-sectional variation that are less likely to be driven by the factors other than the cost of revealing their types (the benefit of mimicking). In the bank-held sample, the result found on the two proxies that identify group of banks that are more sensitive about revealing their types supported the hypotheses that banks' resolution decisions are affected by their concerns of investors' perception. Hence, we expect to find much weaker or no effect for those proxies in a CMBS sample.

As shown in Tables 11 and 12, I do not find significant result for the loan size in less distressed states, the second cross-sectional variation that captures banks' type-revelation sensitivity. Not only the fact that I find evidence in the bank-held sample in the second layer of cross-sectional variation, but also the fact that I do not find evidence in the CMBS sample (the control group) support the hypotheses that banks are hesitant to foreclose large loans because they are concerned about the negative information that may be conveyed to investors.[3][4]

[3]According to Ai and Norton (2003), the coefficient of the interaction terms in non-linear regressions is said to be inaccurate. Nevertheless, there has been active discussion about it, and in contrast, Kolasinski and Siegel (2010) argue the otherwise. In order to address this issue, in Tables 13 and 14, I show test results of both Logit model and Linear Probability model. The OLS regression result shows the similar sign and significance for interaction terms as shown in the Logit model. I also calculated the coefficient of the interaction term in the Logit model using "int eff" stata code, that is suggested by Norton, Wang, and Ai (2004), and the result is marginally insignificant. The reason seems to be having not too many observations of renegotiations in the bank-held sample.

[4]In order to help interpreting test results, I show the results of demeaned models in Tables A.3 and A.4. The tests are centered at the mean value of "LnLoanSize". Demeaned results does not change relations among independent variables and dependent variable, but make interpretations much easier for interaction terms. In Table A.3, for the loans with the average size in the sample, "LessDistState" does not appear to be significant in the Logit model, which means the regional distress levels do not vary renegotiation propensity for loans with the average size. However, in the demeaned linear probability model, the variable appears to be positive and significant. This result suggest that there is a possibility of the banks in the less distressed regions may have better quality loans that are worth renegotiating. In Table A.4, I conduct the same tests in the CMBS sample. The results for "LessDistState" are positive and significant for both the Logit model and the linear probability model. These results support the aforementioned possibility.

Chapter 6

Problem Loan Portfolios

6.1 Relationships with Borrowers

In many cases, in order to save incremental screening and monitoring costs, banks lend money to their existing borrowers. Therefore, it is natural to hypothesize that relationships with borrowers affect banks' resolution decisions on problem loans. Nevertheless, it is not straightforward to predict in which direction these relationships would affect the propensity of foreclosures.

On one hand, it has been well documented in the literature that banks want to keep the relationships with their borrowers well, and vice versa. Therefore, it would be natural to expect the more relationships that banks have with a borrower, the bank is more likely to renegotiate, i.e., take "softer" resolutions.

On the other hand, in the recent financial crisis, banks have had deep concerns about underwater borrowers' strategic defaults. Those strategic defaults of underwater borrowers arose in anticipation of favorable renegotiations of the terms of their loans, and we have actually observed many cases. Therefore, if some banks are known to renegotiate loan terms easily, then the borrowers of the banks will be more likely to strategically default on their loans, expecting their "lenient" banks to decrease their loan amount or extend payment due dates. So, banks may want to keep their reputation as "tough" in order to prevent future defaults. In this case, as banks have more relationships with one borrower, the banks would be more likely to foreclose, i.e., take "tougher" resolutions, so that the borrower will not strategically default on other loans from the bank. Therefore, asking which effect among those two dominates is an interesting empirical question.

For empirical tests, I measure the depths of banks relationships with borrowers in three ways. The first way is simply the number of loans that a bank has with a borrower. "MyManyBorrower" has value of 1 if a borrower has loans more than the median number loans per borrower – 1 in the bank-held sample, 5 in the CMBS sample. This way is easy to understand, but has a caveat of not considering relationships relative to each banks' loan portfolios. For example, having two loans can be consisdered as a very important relationship with one borrower for a small bank, but not so much for a big bank. So, in order to capture the relativeness, the second and the third way measure relationships in each banks' portfolio. "MyBigBorrower" has value of 1 if a borrower's loan share in a bank's problem loan portfolio is larger than the median loan shares of the bank's all borrowers. "MyFreqBorrower" has value of 1 if a borrower's number of loans in a bank's problem loan portfolio is larger than the median number of loans of the bank's all borrowers.

The test I conduct in this section is as follows:

$Logit(Renegotiation = 1)_i = \alpha + \beta 1 * (LnLoanSize)_i + \beta 2 * (LessDistState)_i + \beta 3 * (LessDistState * LnLoanSize)_i + \beta 4 * (MyBorrower)_i + \beta 5 * (MyBorrower * LnLoanSize)_i + Controls_i + \varepsilon$

Table 15 shows the Logit results with bank-held loans. The variables of interest here, regardless how they are defined, show consistent signs and significance. The bigger a borrower is, the more loans a borrower has with a bank, or the larger share of loan amount a borrower has in a bank's problem loan portfolio, the probability of renegotiation increases. Nevertheless, for bigger borrowers, banks are less likely to renegotiate larger loans. I interpret these results as the chance for renegotiations are higher for larger borrowers, either because they simply have many troubled loans with banks, thus increasing the chance, or because banks are more accomodating to keep good relationships. In contrast, the negative sign for the interaction term with loan size suggests that the sample banks were more concerned about having a reputation as tough renegotiators than about keeping good relationships with their big borrowers.

Because of the caveat of the dataset that it does not include the universe of non-troubled loans, I cannot definitively say that "MyManyBorrower," "MyBigBorrower," or "MyFreqBorrower" identifies the actual big borrowers in banks' total loan portfolios. I can only say that they are big borrowers in banks' problem loan portfolios. Then, among healthy or unhealthy big borrowers, it is to unhealthy big borrowers that banks may particularly not want to send signals as being weak, because banks do not want the borrowers with many problem loans to strategically default by learning that their banks are easy renegotiators. Therefore, this could be one reason why we have stronger results for the "tough" reputation motive.

The other variables show consistent signs and significance as the previous tests. Larger loans are more likely to be renegotiated, and the result is stronger among the states with low number of distressed loans. In judical foreclosure states, there is higher chance for renegotiations, due to higher cost of foreclosures. As loans are older, they are more likely to be renegotiated, because the remaining amount of loan will be bigger. If the borrowers of problem loans are in financial distress, they are more likely to be foreclosed.

Table 16 shows the same test results with CMBS loan sample. Similar to the result of bank loan sample, as borrowers have many loans with banks, the chance of renegotiation is higher. As mentioned earlier, because it could be driven from by having simply many troubled loans, the result is not surprising. On the other hand, the results for the interaction between big borrowers and loan sizes differ from what we observed in the bank loan sample, not showing consistent signs or statistical significance.

6.2 Big Players (Borrowers) in the Market

Big players, or large borrowers in commercial real estate markets may have better reputation of having a better business ability and more resources among lenders. In addition, not only the information about their qualities may differ, but also the quantity of information itself can be different. As public firms are less sensitive to informational asymmetry between the firms and outside investors, big players in real estate markets may suffer less from the cost of being opaque.

Therefore, when big players, or large borrowers have troubled loans, their banks may be more likely to renegotiate the problem loans, because the lenders trust more about the borrowers' ability to pay back the loans. Also, because large borrowers must have more resources that they can use to communicate with banks and to use in legal disputes, banks may be more lenient handling large borrowers' problem loans, resulting in a higher propensity to renegotiate.

However, if we consider the above-mentioned limit of the dataset that I only observe problem loans, big borrowers in the sample may or may not coincide with more trustworthy borrowers. More observations in the sample may translate into having more information about them in the market. Nevertheless, we cannot predict the quality of the information. Many observations in the problem loan sample could be simply the result of having more loans in total and being actually big in the market. Or, it could be the result of having particularly more "bad" loans in the market. Considering that we do not see the whole universe of loans, we cannot conclude the meaning of the information whether it means truly big players in the market or truly bad players in the market.

For empirical tests, I identify big borrowers by using the shares of loans in the sample. First, "BigBorrower" has value 1 if a borrower's loan share in the pooled –bank-held sample and CMBS sample– sample is larger than the median of all borrowers' loan shares. By pooling the two dataset, I can identify big players in the commercial real estate market as a whole, regardless of the loan type. Secondly, "MktBigBorrower" has value of 1 if a borrower's loan share in each sample is larger than the median of all borrowers' loan shares in each sample. By separating the two dataset, I can identify better big players for each type of lenders(servicers). Therefore, I test the following model:

$$Logit(Renegotiation = 1)_i = \alpha + \beta 1 * (LnLoanSize)_i + \beta 2 * (LessDistState)_i + \beta 3 * (LessDistState * LnLoanSize)_i + \beta 4 * (BigBorrower)_i + \beta 5 * (BigBorrower * LnLoanSize)_i + Controls_i + \varepsilon$$

Table 17 shows the results of Logit tests. The results suggest that banks are more likely to renegotiate loans of big borrowers in the market. Again, we cannot identify here whether the result is driven by simply having many observations in the sample, or by the banks renegotiate more because they trust more about the big borrowers' financial ability to pay back their loans.

Table 18 shows the same test with the CMBS sample. Interestingly, the interaction term with big borrower and loan sizes show negative and statistically significant coefficients. Considering the fact that special servicers are professionals in handling problem loans, we can assume that they would have better ability analyzing borrowers' true financial ability. Therefore, the result seems that special servicers would have been more hesitant to renegotiate big borrowers' large loans, because they read those big borrowers as bad borrowers.

Big Borrowers and Their Regional Concentration

One can argue that among big players (borrowers), more national players may have better reputations for their superior business skills. Or, more regional players may have closer relationships with regional banks. Therefore, the question of how the big borrowers' regional concentration would affect their trouble loans' resolution is worthwhile to be addressed.

"MktBigBorrower" has value of 1 if a borrower's loan share in each sample is larger than the median of all borrowers' loan shares in each sample. By separating the two dataset, I can identify better big players for each type of lenders(servicers). "ConcBorrower_Loan (_State, _Mkt, _SubMkt)" has value of 1 if the Herfindhal measure of loan share, i.e., the summation of squared loan (in each states, markets, submarkets, respectively) shares in each borrower's total problem loans in each sample, is larger than the median of each sample. I test the following model:

$$Logit(Renegotiation = 1)_i = \alpha + \beta 1 * (LnLoanSize)_i + \beta 2 * (LessDistState)_i + \beta 3 * (LessDistState * LnLoanSize)_i + \beta 4 * (MktBigBorrower)_i + \beta 5 * (ConcBorrower)_i + \beta 6 * (MktBigBorrower * ConcBorrower)_i + Controls_i + \varepsilon$$

Table 19 shows the relation between big borrowers' regional concentration and renegotiation tendency in the bank-held sample. The negative and significant coefficient for the interaction term of "MktBigBorrower" and "ConcBorrower" suggest that the sample banks renegotiated less if big borrowers have more regionally clustered properties and mortgages. The result may imply that banks valued big borrowers' having more regionally diversified or scattered properties. This could result from the borrowers' having better reputation as national players, or from their more diversification of assets. Also, it is possible that the sample banks worried the news of renegotiations for more regionally clustered big borrowers would travel faster to other borrowers in the close region.

Table 20 shows the same tests run for the CMBS sample. Interestingly, the interaction term of "MktBigBorrower" and "ConcBorrower" is not significant. This result adds more support of banks' concerns of strategic defaults or negative spillovers as the behind reason for Table 18 results with the bank-held sample.

6.3 Geographical Diversification of Problem Loan Portfolios and Negative Spillovers

Many studies around the recent financial crisis document the negative spillover of foreclosures on nearby properties. If a property is foreclosed, then the properties that are in the neighborhood will suffer price drops. The price drops are often called as negative spillovers. There are several possible reasons behind negative spillovers.

The first reason is that in times like the recent crisis where we have experienced not much increase in demand for properties, but a sudden increase in supply of properties, as a result of demand and supply, an additional property for sale will only exacerbate the dropping property prices.

The second reason is possible vandalism. It is documented in the literature that there have been cases where the previous owners of foreclosed properties did not leave the properties right after the foreclosures, still living in the houses for a while, not taking a good care of the properties. Also, if a foreclosed property is left empty for a long time, then the around area will not be taken care of, turning into a bad shape.[1]

When banks determine resolutions on problem loans, if a resolution of one loan possibly affects other loans there loan portfolio, the banks may decide to choose different resolutions depending on the size of externalities. A resolution may be optimal for one problem loan, maximizing the loan's economic value, nevertheless, the negative externality on other loans can be so big that the resolution may fail to maximize the loan portfolio's value. In that case, a bank may decide to take other resolution, taking the big picture into consideration.

The aforementioned negative spillover will affect more heavily banks with highly-geographically-concentraded loan portfolios. If a bank has a problem loan portfolio that consists of one loan in each state, then it is highly unlikely that a foreclosure in a state will push down the price of other collateral property in a different state. Hence, as banks have more geographically diversified loan portfolios, the more the banks become prone to foreclose on problem loans, free from the concerns of negative spillovers.[2]

[1] See Lee (2008).

[2] The question of negative spillovers can be tested cross-sectionally in two ways. The first way is to test across banks with different levels of geographical diversification in problem loan portfolios. The second way is to test across regions with different levels of over-supply of properties for sale. In order to precisely measure the foreclosure pressure, I need to know the supply of for-sale properties and actual transactions. With the limitation that I do not observe for-sale properties and transactions, I cannot conduct the second cross-sectional test. Currently, the tests of "Less Distressed States" are equivalent to the second cross-sectional test, if I use foreclosures information

Similar to Schoar (2002), I measure the degree of geographical diversification of loan portfolios using the number of loans in portfolios and Herfindhal-type concentration measures of loan shares in portfolios acorss loan, state, market, and submarket levels. "ManyLoanPf" has value of 1 if a bank's (special servicer's) loan portfolio has more loans than the median number of loans per bank (special servicer) –the median is 3 for the bank-held sample and 28 for the CMBS sample. "ConcPf_Loan (_State, _Mkt, _SubMkt) has value of 1 if the Herfindhal measure of loan share, i.e., the summation of squared loan (in each states, markets, submarkets, respectively) shares in each bank's (special servicer's) total problem loan portfolio, is larger than the median of each sample. "ImpactOnSubMkt" is the relative size of a loan normalized by the summation of all loans in the respective submarket, assuming that the price impact, i.e., the negative spillover, is strongest in the closest region.

The test that I run in this section is as follows:

$$Logit(Renegotiation = 1)_i = \alpha + \beta 1 * (LnLoanSize)_i + \beta 2 * (LessDistState)_i + \beta 3 * (LessDistState * LnLoanSize)_i + \beta 4 * (ConcPf)_i + \beta 5 * (ConcPf * LnLoanSize)_i + Controls_i + \varepsilon$$

Table 21 shows the result of Logit model tests of the importance of geographical diversification in banks' foreclosure decisions due to a negative spillover effect of foreclosures. As banks have a smaller number of loans in their problem loan portfolios, or higher Herfindhal measures, they are more likely to have more geographically

in the sample. There is one-to-one correlation of states with most number of distressed properties and foreclosed properties in the sample.

concentrated problem loan portfolios. The result suggest that banks are more likely to renegotiate larger loans if they have geographically concentrated problem loan portfolios.

Table 22 shows the same tests for the CMBS sample. The geographical concentration does not show any significance. The result is expected, because special servicers are compensated by the amount of trouble loans that they are handling. The payoff of total problem loans would affect special servicers' wealth much less than it would affect banks' wealth. Therefore, special servicers would be free from the concern of negative spillover of foreclosures on other loans in their portfolios.

In order to more clearly test how banks are concerned about the spillover on their shadow inventory, I use relative size of loans compared to the total problem loans' size in the nearby neighborhood. In Table 23, the positive and significant coefficient for the interaction term of geographical concentration and the relative size (impact) on the total nearby problem loan portfolios mean that as banks have geographically concentrated problem loan portfolio, they are more likely to renegotiate loans that have big impact on their problem loan portfolios in the close regions. The much weaker or insignificant result in Table 24 suggest that banks seem to importantly consider the negative spillover effect of foreclosures on their shadow inventories.

Chapter 7

Conclusion

This thesis studies banks' resolution of problem mortgage loans. I examine how banks' signaling concerns under information asymmetry, banks' relationships with borrowers, and the negative spillover of foreclosures may affect their resolution decisions. With a noble dataset of problem commercial mortgage loans, I provide empirical findings consistent with both the theory and conventional wisdom from the recent financial crisis.

Since September 2007, we have experienced a crisis that was triggered by decreasing real estate prices, and banks have been at the center of the crisis. Unprecedented plummeting real estate prices triggered numerous problem real estate loans, and the banks that owned such loans have been swamped with problems needing to be addressed. These banks have been faced with resolution decisions that can maximize the economic value of those problem loans, but that may also reveal something about the true value of their assets.

In a frictionless economy with no information asymmetry, the value of a firm is determined only by the value of its assets (Modigliani and Miller (1958)). Hence, firms choose optimal actions that maximize the net present value of their assets. However, with informational asymmetry, outside investors cannot directly observe the true value of firms. In such circumstances, investors infer a firm's true value or true type by observing its actions, which in turn gives poor quality firms an incentive to choose otherwise sub-optimal actions to mimic the behavior of high-valued firms.

I study banks' choices between foreclosures and renegotiations of problem loans when banks are concerned about the negative information that may be conveyed to investors through foreclosures. Because of informational frictions, investors cannot directly observe either banks' true ability or true value of banks' loan portfolio. Under information asymmetry, investors have to infer the quality of loans from looking at which actions have been taken. Therefore, when banks with bad quality assets have a mimicking motive, they would tend to mimic the actions of banks with better quality assets in the way they resolve problem loans, and investors will not be able to accurately infer banks' true asset values.

Consistent with banks renegotiating excessively to avoid a reputational hit, I find that banks are more likely to renegotiate (rather than foreclose) a large distressed loan than a small one, other things being equal. Of course, there could be other factors that are correlated with loan size that cause differences in the resolution decision.

To address this possibility, I utilize three additional sources of cross-sectional variation. I find that the size difference is sharper when there is more reputational capital at stake, either because the bank in question had better recent performance or because the loan is in a region with fewer distressed properties. In addition, I find that banks that raised new equity capital exhibit a stronger tendency to renegotiate larger problem loans in the previous year. And, this relation is much weaker for other types of capital raising, suggesting that relatively healthy banks that can afford to raise capital through other types of financing are less concerned about revealing negative information through large foreclosures.

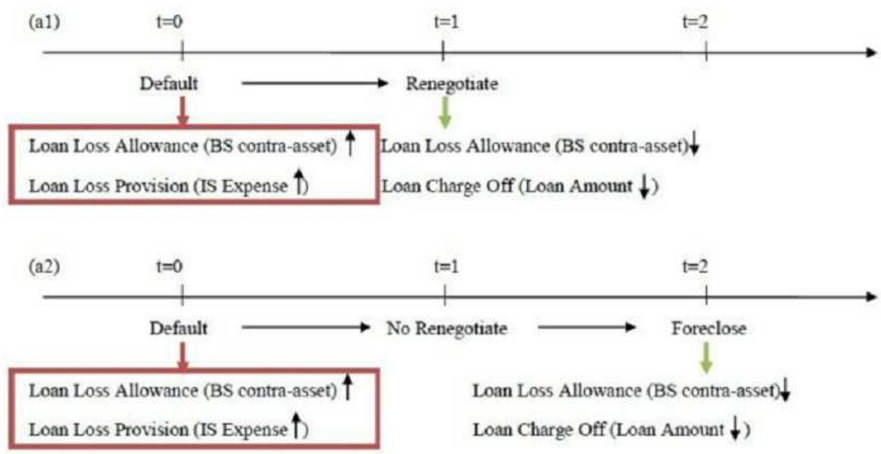
I conduct a falsification test in which I repeat the analysis using a sample of mortgages in Commercial Mortgage Backed Securities (CMBS). The servicers of CMBS loans are not the originators, so they do not face concerns about inference of upfront screening ability that originating banks face. I find that the results are weaker or not present for CMBS, in contrast to the bank loan sample.

Lastly, I study banks' resolution of problem loans while considering their problem loan portfolios. I consider two aspects of banks' problem loan portfolios – their relationships with borrowers and the degree of regional diversification. First, empirical results suggest that the sample banks chose to act "tougher", i.e., foreclose more, as they have more loans with a borrower. The results appear to be consistent with what we have observed in the recent financial crisis, as lenders have been deeply concerned of many underwater borrowers' strategic defaults.

Secondly, the degree of geographical diversification in problem loan portfolios may affect banks' resolution decisions. I find that as banks have geographically concentrated problem loan portfolios, they are more likely to renegotiate larger –both absolutely and relatively– loans. This result is consistent with the banks being concerned about the negative spillover of foreclosures on other assets in their problem loan portfolios.

Figure 1: Timing of Loan Loss Recognitions on Balance Sheets

a.



b.

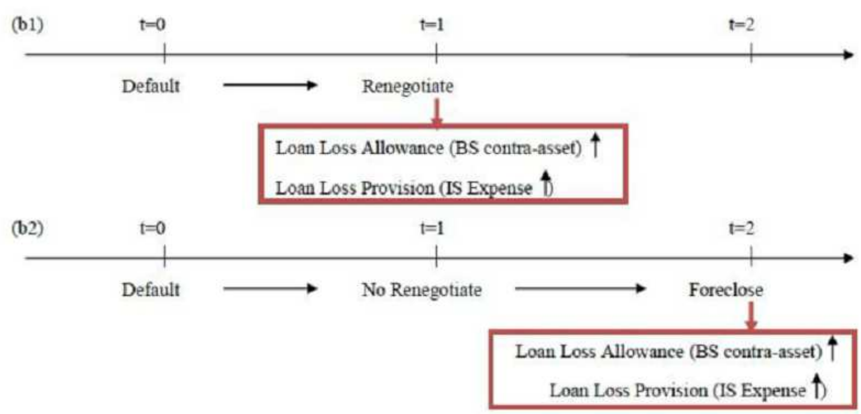


Figure 2: Frequencies of Resolution Initiations in the Bank-held Sample

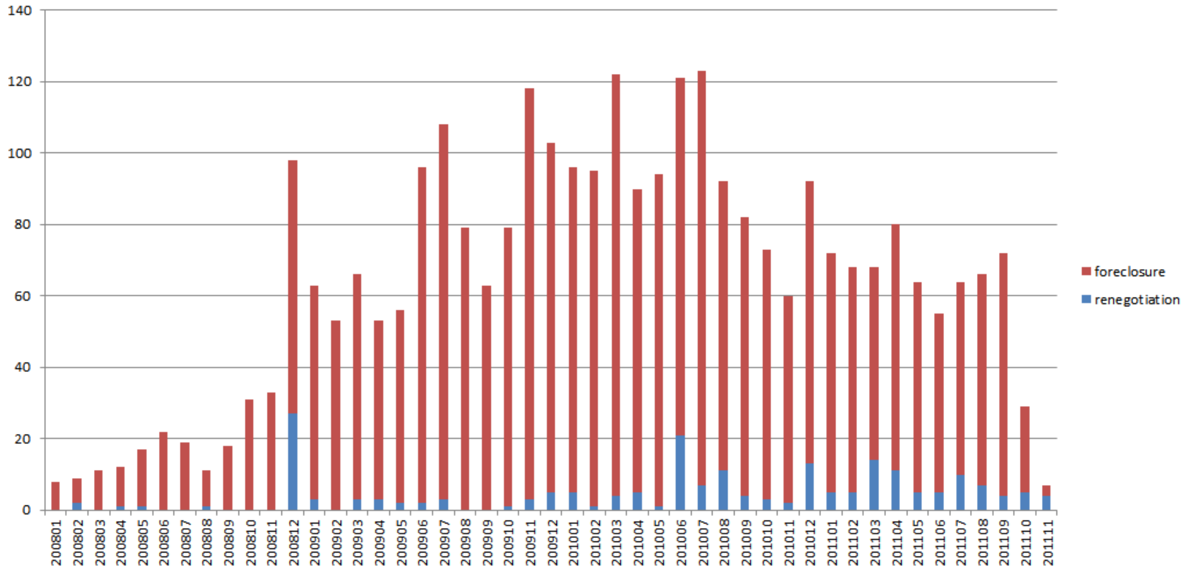


Figure 3: Frequencies of Resolution Initiations in the CMBS Sample

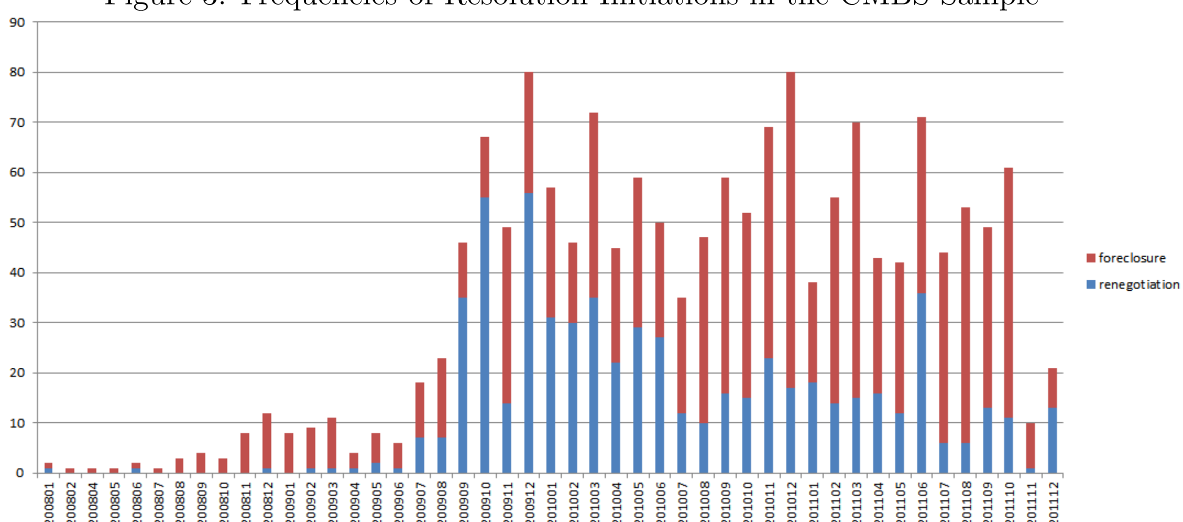


Table 1: Summary Statistics of Bank-held Sample

Table 1 shows frequency, average loan size, and average duration of different resolutions in the bank-held sample. *Beingserviced* means it is specified in the data that a loan is in the process of resolving the troubled situation, but without an indication of any specific resolution has been taken yet. *Foreclosure* means a problem loan is either foreclosure initiated or completed. I define *Renegotiation* as the resolutions of refinancing, forbearance, extension, or restructuring.

Frequency of Resolutions

Resolution	Freq.	Percent	Cum.
Beingserviced	237	5.4	5.4
Foreclosure	3415	77.81	83.21
Others	438	9.98	93.19
Renegotiation	299	6.81	100
Total	4389	100	

Size(in $millions) of Resolutions

Resolution	N	mean	sd	min	p25	p50	p75	max
Beingserviced	211	19.78	32.98	0.4	4.28	8.70	17.30	216.50
Foreclosure	3173	11.66	22.46	0	2.70	5.00	11.40	365.00
Others	282	29.15	74.03	0.1	3.87	7.65	23.10	700.00
Renegotiation	273	36.56	68.47	0.3	6.27	17.90	35.50	677.33
Total	3939	15.08	35.16	0	2.96	5.70	13.70	700.00

t-test	Diff	t stat
LnLoanSize(Foreclosure)-LnLoanSize(Renegotiation, Others)	-0.6766	-13.08
LnLoanSize(Foreclosure)-LnLoanSize(Renegotiation)	-0.9516	-11.11

Duration(#months) of Resolutions

Resolution	N	mean	sd	min	p25	p50	p75	max
Foreclosure	2263	2.80	7.02	0	0	0	3	142
Others	102	3.66	7.44	0	0	0	3	31
Renegotiation	226	1.44	4.79	0	0	0	0	38
Total	2591	2.71	6.88	0	0	0	3	142

t-test	Diff	t stat
Duration(Foreclosure)-Duration(Renegotiation, Others)	0.6691	1.89
Duration(Foreclosure)-Duration(Renegotiation)	1.3591	3.87

Table 2: Bank-held Sample: Loan Size and Duration by Resolutions

This table shows the stylized facts of *LnLoanSize* and *Duration* differences by Resolution types in the data. *LnLoanSize* is ln(loan size in $millions). *Duration* is the number of months spent since a loan has become delinquent until a resolution action has been taken. Panel A is a linear probability model that regresses choices of foreclosures or renegotiations on the loan's size. Among four possible resolution outcomes-foreclosure, renegotiation, others, and beingserviced- if a loan has been foreclosed, the indicator variable, *Foreclosed* has value of 1. If a loan has been renegotiated, the indicator variable, *Renegotiated* has value of 1. Panel B is OLS regression of *Duration* on the indicator variable, *Foreclosed* or *Renegotiated*. In order to magnify the difference between foreclosed or renegotiated loans, Panel C is testing the same as Panel B conditioning on the resolution being either *Foreclosed* or *Renegotiated*. Standard errors are clustered at the property level.

Panel A	(1) Foreclosed	(2) Renegotiated
LnLoanSize	-0.0765***	0.0410***
	(0.00612)	(0.00456)
Constant	0.950***	-0.00807
	(0.0120)	(0.00783)
N	3934	3934
R^2	0.0517	0.0361

Panel B	(1) Duration	(2) Duration
Foreclosed	0.669*	
	(0.353)	
Renegotiated		-1.396***
		(0.347)
Constant	2.128***	2.834***
	(0.317)	(0.151)
N	2591	2591
R^2	0.0010	0.0033

Panel C	(1) Duration
Foreclosed	1.359***
	(0.349)
Constant	1.438***
	(0.313)
N	2489
R^2	0.0032

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Bank-held Sample, Binary Logit: Renegotiation Size Sensitivity in Less Distressed States

This table shows the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. Standard errors are clustered at the property level.

Base outcome: Foreclosure		
Renegotiation	LnLoanSize	0.251**
		(0.108)
	LessDistState	-2.168**
		(0.899)
	LessDistState*LnLoanSize	1.229***
		(0.355)
	Judicial	0.656**
		(0.255)
	LoanAge	-0.0988***
		(0.0106)
	DistBorrower	-13.77***
		(0.501)
	Constant	-0.352
		(0.300)
	N	1109

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Bank-held Sample, Competing Risks Model: Renegotiation Size Sensitivity in Less Distressed States

This table shows the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a competing risks model. There are two possible resolution outcomes-foreclosure or renegotiation. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is the age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. Standard errors are clustered at the bank(lender) level.

Competing Risk: Foreclosure		(1)	(2)
Renegotiation	LnLoanSize	0.616^{***}	0.155^{**}
		(0.101)	(0.0749)
	LessDistState		-0.839
			(0.519)
	LessDistState*LnLoanSize		0.450^{**}
			(0.185)
	Judicial		0.502^{***}
			(0.180)
	LoanAge		-0.0723^{***}
			(0.00942)
	DistBorrower		-19.01^{***}
			(0.686)
	N	2354	901

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Commercial Bank-held Sample, Binary Logit: Renegotiation Size Sensitivity in High ROA Banks

Table 5 tests the relation of a loan's size and a renegotiation decision and how the relation interacts with the bank's ROA level, using a binary logit model. There are two possible resolution outcomes- foreclosure or renegotiation- and the base outcome in the test is foreclosure. In this sample, I can control for more specific characteristics of banks. *LnLoanSize* is ln(loan size in $millions). *HighROA* is an indicator variable of value 1 if a bank's ROA is above the median, 0 if below median. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is the age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *LnBankSize* is ln(Total Assets in $000). *LLA* is the ratio of loan loss allowance/total loan. *DEF* is the ratio of problem loan/total loan measured as (delinquent loan + non accruing loan)/total loan. *RED* is the fraction of real estate problem loan in the problem loan measured as (real estate delinquent loan + real estate non accruing loan)/(delinquent loan + non accruing loan). All variables using accounting information is at the closest quarter-end value right before the resolution decision. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)	(4)
Renegotiation	LnLoanSize	-0.0169	0.362	-3.870***	-2.343**
		(0.270)	(0.357)	(1.474)	(1.118)
	HighROA			1.887	-1.291
				(4.069)	(2.023)
	HighROA*LnLoanSize			8.459***	6.612***
				(2.461)	(1.489)
	Judicial		1.064	1.632	0.450
			(0.721)	(2.311)	(1.133)
	LoanAge		-0.165***	-0.745**	-0.557***
			(0.0387)	(0.312)	(0.0823)
	DistBorrower		-6.441***	22.68	16.93***
			(2.315)	(17.46)	(5.974)
	LnBankSize			5.193***	4.252***
				(2.008)	(0.685)
	LLA				28.67
					(26.68)
	DEF				-31.89
					(22.88)
	RED			6.737***	8.340***
				(2.396)	(2.661)
	Constant	-2.426***	0.526	-71.43**	-59.97***
		(0.393)	(0.656)	(27.74)	(10.26)
	N	427	177	130	130

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Commercial Bank-held Sample, Binary Logit: Renegotiation Size Sensitivity in Less Distressed States

This table shows the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is the age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *LnBankSize* is ln(Total Assets in $000). *LLA* is the ratio of loan loss allowance/total loan. *DEF* is the ratio of problem loan/total loan measured as (delinquent loan + non accruing loan)/total loan. *RED* is the fraction of real estate problem loan in the problem loan measured as (real estate delinquent loan + real estate non accruing loan)/(delinquent loan + non accruing loan). All variables using accounting information is at the closest quarter-end value right before the resolution decision. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)
Renegotiation	LnLoanSize	-0.235	-0.552	0.287
		(0.343)	(0.372)	(0.271)
	LessDistState	-3.488	-2.550	-6.000**
		(2.129)	(2.317)	(2.512)
	LessDistState*LnLoanSize	3.992**	3.807**	4.335***
		(1.786)	(1.812)	(1.506)
	Judicial	0.174	0.360	-1.592
		(0.927)	(1.375)	(1.086)
	LoanAge	-0.323***	-0.267***	-0.402***
		(0.101)	(0.0874)	(0.124)
	DistBorrower	3.131	-0.834	8.624
		(6.481)	(4.830)	(9.112)
	LnBankSize	2.354***	1.904***	2.816***
		(0.547)	(0.454)	(0.773)
	LLA	38.75**		60.61***
		(18.87)		(22.55)
	DEF	-31.26***		-58.34***
		(11.72)		(22.07)
	RED		-1.307	5.248**
			(1.698)	(2.438)
	Constant	-29.54***	-23.57***	-37.86***
		(7.303)	(6.366)	(10.86)
	N	130	130	130

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Banks' Capital Raising Activities and Resolution Decisions

This table shows, in the bank-held sample, the relation of renegotiation decisions and capital raising activities using a binary logit model. By linking next year's capital raising frequency and this year's resolution decisions, I attempt to see whether the different degree of signaling concerns affected their foreclosure or renegotiation decisions. There are two possible resolution outcomes- foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. From SNL dataset, I look at banks' capital raising activities. Among different types of capital, I look at common equity, preferred equity, senoir debt, and subsidiary trust preferred. *FreqCapRaising* has value of 1 if banks raised a certain type of capital more frequently than the median frequency in the next year. The medians in the matched sample for common equity, preferred equity, senior debt, and subsidiary trust preferred are 2, 1, 104, 2, respectively. Standard errors are clustered at the property level.

Base outcome: Foreclosure		Common Equity	Preferred Equity	Senior Debt	Subsidiary Trust Preferred
Renegotiation	LnLoanSize	0.293**	0.324***	0.326***	0.324***
		(0.119)	(0.119)	(0.119)	(0.116)
	LessDistState	-2.113**	-2.018**	-1.972**	-2.029**
		(0.976)	(0.973)	(0.959)	(0.969)
	LessDistState*LnLoanSize	1.260***	1.210***	1.203***	1.214***
		(0.397)	(0.394)	(0.390)	(0.393)
	FreqCapRaising	-4.090	1.289	-1.320	-9.862***
		(3.398)	(0.967)	(2.019)	(0.939)
	FreqCapRaising*LnLoanSize	2.087*	-0.194	0.228	-3.311**
		(1.151)	(0.367)	(0.499)	(1.363)
	Judicial	0.807***	0.848***	0.832***	0.841***
		(0.266)	(0.265)	(0.264)	(0.263)
	LoanAge	-0.119***	-0.117***	-0.117***	-0.117***
		(0.0148)	(0.0143)	(0.0144)	(0.0143)
	DistBorrower	-12.85***	-13.76***	-12.60***	-12.77***
		(0.558)	(0.554)	(0.569)	(0.553)
	Constant	-0.282	-0.389	-0.356	-0.368
		(0.300)	(0.302)	(0.300)	(0.300)
	N	1086	1086	1086	1086
	pseudo R^2	0.5069	0.5016	0.5012	0.5004

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Banks' Capital Raising Activities and Resolution Decisions

This table shows, in the bank-held sample, the relation of renegotiation decisions and capital raising activities using a binary logit model. By linking current year's capital raising frequency and current year's resolution decisions, I attempt to see whether the different degree of signaling concerns affected their foreclosure or renegotiation decisions during or right after capital raising activities. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. From SNL dataset, I look at banks' capital raising activities. Among different types of capital, I look at common equity, preferred equity, senoir debt, and subsidiary trust preferred. *FreqCapRaising* has value of 1 if banks raised a certain type of capital more frequently than the median frequency in the current year. Standard errors are clustered at the property level.

Base outcome: Foreclosure		Common Equity	Preferred Equity	Senior Debt	Subsidiary Trust Preferred
Renegotiation	LnLoanSize	0.329***	0.324***	0.313***	0.332***
		(0.115)	(0.116)	(0.122)	(0.116)
	LessDistState	-2.004**	-2.007**	-2.003**	-1.982**
		(0.954)	(0.967)	(0.963)	(0.964)
	LessDistState*LnLoanSize	1.204***	1.210***	1.211***	1.202***
		(0.388)	(0.392)	(0.391)	(0.391)
	FreqCapRaising	-12.62***	-0.186	-1.180	10.95***
		(0.850)	(1.949)	(1.614)	(2.127)
	FreqCapRaising*LnLoanSize	-0.726**	0.930	0.415	-10.88***
		(0.363)	(0.884)	(0.473)	(2.373)
	Judicial	0.829***	0.844***	0.845***	0.852***
		(0.264)	(0.266)	(0.264)	(0.264)
	LoanAge	-0.116***	-0.117***	-0.117***	-0.116***
		(0.0142)	(0.0143)	(0.0144)	(0.0143)
	DistBorrower	-13.94***	-14.31***	-12.03***	-12.79***
		(0.600)	(0.939)	(0.555)	(0.551)
	Constant	-0.369	-0.389	-0.355	-0.407
		(0.299)	(0.303)	(0.301)	(0.302)
	N	1086	1086	1086	1086
	pseudo R^2	0.5041	0.5015	0.5008	0.5030

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Summary Statistics of CMBS Sample

Table 7 shows frequency, average loan size, and average duration of different resolutions in the CMBS sample. *Beingserviced* means it is specified in the data that a loan is in the process of resolving the troubled situation, but without an indication of any specific resolution has been taken yet. *Foreclosure* means a problem loan is either foreclosure initiated or completed. I define *Renegotiation* as the resolutions of refinancing, forbearance, extension, or restructuring.

Frequency of Resolutions

Resolution	Freq.	Percent	Cum.
Beingserviced	2240	44.08	44.08
Foreclosure	1005	19.78	63.85
Others	819	16.12	79.97
Renegotiation	1018	20.03	100
Total	5082	100	

Size(in $millions) of Resolutions

Resolution	N	mean	sd	min	p25	p50	p75	max
Beingserviced	2107	15.18	30.86	0.10	3.70	6.80	14.15	506.53
Foreclosure	936	19.39	40.87	0.30	4.36	8.49	17.71	491.08
Others	806	10.29	40.80	0.40	1.30	2.05	3.80	516.22
Renegotiation	910	34.64	58.80	0.70	6.52	12.00	33.65	537.30
Total	4759	18.90	41.93	0.10	3.20	6.88	15.86	537.30

t-test	Diff	t stat
LnLoanSize(Foreclosure)-LnLoanSize(Renegotiation, Others)	0.2441	5.91
LnLoanSize(Foreclosure)-LnLoanSize(Renegotiation)	-2.3604	-8.67

Duration(#months) of Resolutions

Resolution	N	mean	sd	min	p25	p50	p75	max
Foreclosure	983	7.38	8.64	0	0	4	13	49
Others	815	19.91	5.27	0	22	22	22	38
Renegotiation	707	10.31	20.33	0	2	8	12	327
Total	2505	12.29	13.58	0	3	11	22	327

t-test	Diff	t stat
Duration(Foreclosure)-Duration(Renegotiation, Others)	-8.0745	-16.96
Duration(Foreclosure)-Duration(Renegotiation)	-2.9331	-3.6

Table 10: CMBS Sample: Loan Size and Duration by Resolutions

This table shows the stylized facts of *LnLoanSize* and *Duration* differences by Resolution types in the CMBS data. *LnLoanSize* is ln(loan size in $millions). *Duration* is the number of months spent since a loan has become delinquent until a resolution action has been taken. Panel A is a linear probability model that regresses choices of foreclosures or renegotiations on the loan's size. Among four possible resolution outcomes-foreclosure, renegotiation, others, and beingserviced- if a loan has been foreclosed, the indicator variable, *Foreclosed* has value of 1. If a loan has been renegotiated, the indicator variable, *Renegotiated* has value of 1. Panel B is OLS regression of *Duration* on the indicator variable, *Foreclosed* or *Renegotiated*. In order to magnify the difference between foreclosed or renegotiated loans, Panel C is testing the same as Panel B conditioning on the resolution being either *Foreclosed* or *Renegotiated*. Standard errors are clustered at the property level.

Panel A	(1) Foreclosed	(2) Renegotiated
LnLoanSize	0.0252***	0.0839***
	(0.00453)	(0.00515)
Constant	0.146***	0.0209**
	(0.0102)	(0.0105)
N	4759	4759
R^2	0.0061	0.0697

Panel B	(1) Duration	(2) Duration
Foreclosed	-8.075***	
	(0.482)	
Renegotiated		-2.749***
		(0.798)
Constant	15.45***	13.06***
	(0.387)	(0.232)
N	2505	2505
R^2	0.0844	0.0083

Panel C	(1) Duration
Foreclosed	-2.933***
	(0.815)
Constant	10.31***
	(0.764)
N	1690
R^2	0.0096

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: CMBS Sample, Binary Logit: Renegotiation Size Sensitivity in Less Distressed States

Table 9 shows, in CMBS sample, the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. Standard errors are clustered at the property level.

Base outcome: Foreclosure		
Renegotiation	LnLoanSize	0.361***
		(0.0673)
	LessDistState	0.277
		(0.278)
	LessDistState*LnLoanSize	0.0266
		(0.106)
	Judicial	-0.0449
		(0.127)
	LoanAge	-0.0213***
		(0.00201)
	DistBorrower	-1.568***
		(0.426)
	Constant	0.148
		(0.200)
	N	1690

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: CMBS Sample, Competing Risks Model: Renegotiation Size Sensitivity in Less Distressed States

This table shows the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a competing risks model in the CMBS sample. There are two possible resolution outcomes-foreclosure or renegotiation. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is the age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. Standard errors are clustered at the bank(lender) level.

Competing Risk: Foreclosure		(1)	(2)
Renegotiation	LnLoanSize	0.453***	0.453***
		(0.0624)	(0.0876)
	LessDistState		0.0582
			(0.378)
	LessDistState*LnLoanSize		-0.00133
			(0.0991)
	Judicial		-0.0213
			(0.0654)
	LoanAge		-0.00929*
			(0.00494)
	DistBorrower		-21.92***
			(0.564)
N		1396	1270

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Bank-held Sample: Logit Models and Linear Probability Models

This table shows, in the bank-held sample, the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a binary logit model and linear probability model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. Standard errors are clustered at the property level.

		Bank-held Sample		
Base outcome: Foreclosure		Logit Coefficient	Logit Odds Ratio	Linear Prob Model
Renegotiation	LnLoanSize	0.251^{**}	1.285^{**}	0.0161^{*}
		(0.108)	(0.139)	(0.00870)
	LessDistState	-2.168^{**}	0.114^{**}	-0.126^{***}
		(0.899)	(0.103)	(0.0471)
	LessDistState*LnLoanSize	1.229^{***}	3.417^{***}	0.108^{***}
		(0.355)	(1.214)	(0.0274)
	Judicial	0.656^{**}	1.926^{**}	0.0401^{*}
		(0.255)	(0.492)	(0.0237)
	LoanAge	-0.0988^{***}	0.906^{***}	-0.00444^{***}
		(0.0106)	(0.010)	(0.000459)
	DistBorrower	-13.77^{***}	0.000^{***}	-0.0696
		(0.501)	(0.000)	(0.0460)
	Constant	-0.352	-0.352	0.249^{***}
		(0.300)	(0.300)	(0.0292)
	N	1109	1109	1109
	(pseudo) R^2	0.4299	0.4299	0.2120

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: CMBS Sample: Logit Models and Linear Probability Models

This table shows, in the CMBS sample, the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a binary logit model and linear probability model. There are two possible resolution outcomes-foreclosure or renegotiation-and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. Standard errors are clustered at the property level.

		CMBS Sample		
Base outcome: Foreclosure		Logit Coefficient	Logit Odds Ratio	Linear Prob Model
Renegotiation	LnLoanSize	0.361^{***}	1.435^{***}	0.0801^{***}
		(0.0673)	(0.097)	(0.0142)
	LessDistState	0.277	1.319	0.0693
		(0.278)	(0.366)	(0.0581)
	LessDistState*LnLoanSize	0.0266	1.027	0.00286
		(0.106)	(0.109)	(0.0212)
	Judicial	-0.0449	0.956	-0.00821
		(0.127)	(0.121)	(0.0278)
	LoanAge	-0.0213^{***}	0.979^{***}	-0.00452^{***}
		(0.00201)	(0.002)	(0.000349)
	DistBorrower	-1.568^{***}	0.208^{***}	-0.300^{***}
		(0.426)	(0.089)	(0.0636)
	Constant	0.148	0.148	0.522^{***}
		(0.200)	(0.200)	(0.0435)
	N	1690	1690	1690
	(pseudo) R^2	0.0949	0.0949	0.1217

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Bank-held Sample, Binary Logit: Relationships with Borrowers

This table shows, in the bank-held sample, the relation of renegotiation decisions and relationships with borrowers, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *MyManyBorrower* has value of 1 if a borrower has loans more than the median number loans per borrower – 1 in the bank-held sample, 5 in the CMBS sample–. *MyBigBorrower* has value of 1 if a borrower's loan share in a bank's problem loan portfolio is larger than the median loan shares of the bank's all borrowers. *MyFreqBorrower* has value of 1 if a borrower's number of loans in a bank's problem loan portfolio is larger than the median number of loans of the bank's all borrowers. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)
Renegotiation	LnLoanSize	0.407***	0.568***	0.421***
		(0.141)	(0.187)	(0.133)
	LessDistState	-2.113**	-2.128**	-1.832**
		(0.966)	(0.922)	(0.924)
	LessDistState*LnLoanSize	1.227***	1.208***	1.111***
		(0.390)	(0.355)	(0.374)
	MyManyBorrower	0.652		
		(0.439)		
	MyManyBorrower*LnLoanSize	-0.450**		
		(0.198)		
	MyBigBorrower		0.866*	
			(0.496)	
	MyBigBorrower*LnLoanSize		-0.527**	
			(0.229)	
	MyFreqBorrower			2.151***
				(0.486)
	MyFreqBorrower*LnLoanSize			-0.796***
				(0.219)
	Judicial	0.578**	0.666**	0.432
		(0.268)	(0.271)	(0.281)
	LoanAge	-0.0980***	-0.0976***	-0.0928***
		(0.0106)	(0.0109)	(0.0107)
	DistBorrower	-12.07***	-11.55***	-12.42***
		(0.518)	(0.729)	(0.740)
	Constant	-0.600*	-0.679*	-0.674*
		(0.353)	(0.379)	(0.355)
	N	1107	929	929
	pseudo R^2	0.4338	0.4423	0.4461

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: CMBS Sample, Binary Logit: Relationships with Borrowers

This table shows, in the CMBS sample, the relation of renegotiation decisions and relationships with borrowers, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *MyManyBorrower* has value of 1 if a borrower has loans more than the median number loans per borrower – 1 in the bank-held sample, 5 in the CMBS sample–. *MyBigBorrower* has value of 1 if a borrower's loan share in a bank's problem loan portfolio is larger than the median loan shares of the bank's all borrowers. *MyFreqBorrower* has value of 1 if a borrower's number of loans in a bank's problem loan portfolio is larger than the median number of loans of the bank's all borrowers. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)
Renegotiation	LnLoanSize	0.468***	0.906***	0.483***
		(0.0805)	(0.198)	(0.0934)
	LessDistState	0.0923	-0.0533	-0.0893
		(0.296)	(0.363)	(0.377)
	LessDistState*LnLoanSize	0.0348	0.169	0.144
		(0.111)	(0.125)	(0.135)
	MyManyBorrower	0.987***		
		(0.295)		
	MyManyBorrower*LnLoanSize	0.130		
		(0.116)		
	MyBigBorrower		2.206***	
			(0.473)	
	MyBigBorrower*LnLoanSize		-0.713***	
			(0.212)	
	MyFreqBorrower			1.349***
				(0.373)
	MyFreqBorrower*LnLoanSize			-0.113
				(0.132)
	Judicial	-0.0610	-0.0320	0.0301
		(0.132)	(0.154)	(0.155)
	LoanAge	-0.0176***	-0.0161***	-0.0169***
		(0.00228)	(0.00283)	(0.00286)
	DistBorrower	-2.076***	-0.585	-0.907*
		(0.386)	(0.547)	(0.499)
	Constant	-0.823***	-1.890***	-1.123***
		(0.250)	(0.431)	(0.297)
	N	1635	1187	1187
	pseudo R^2	0.1372	0.1183	0.1367

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Bank-held Sample, Binary Logit: Big Borrowers in the Market

This table shows, in the bank-held sample, the relation of renegotiation decisions and sizes of borrowers in the market, using a binary logit model. There are two possible resolution outcomes- foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *BigBorrower* has value 1 if a borrower's loan share in the pooled –bank-held sample and CMBS sample– sample is larger than the median of all borrowers' loan shares. *MktBigBorrower* has value of 1 if a borrower's loan share in each sample is larger than the median of all borrowers' loan shares in each sample. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)
Renegotiation	LnLoanSize	-0.0826	0.0249
		(0.202)	(0.205)
	LessDistState	-1.550*	-1.633*
		(0.828)	(0.850)
	LessDistState*LnLoanSize	1.011***	1.016***
		(0.325)	(0.331)
	BigBorrower	1.615***	
		(0.531)	
	BigBorrower*LnLoanSize	-0.0107	
		(0.246)	
	MktBigBorrower		1.663***
			(0.561)
	MktBigBorrower*LnLoanSize		-0.125
			(0.253)
	Judicial	0.536**	0.531**
		(0.271)	(0.270)
	LoanAge	-0.0928***	-0.0931***
		(0.0105)	(0.0105)
	DistBorrower	-13.14***	-13.18***
		(0.482)	(0.494)
	Constant	-0.369	-0.450
		(0.392)	(0.400)
	N	1093	1093
	pseudo R^2	0.4552	0.4489

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: CMBS Sample, Binary Logit: Big Borrowers in the Market

This table shows, in the CMBS sample, the relation of renegotiation decisions and sizes of borrowers in the market, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *BigBorrower* has value 1 if a borrower's loan share in the pooled –bank-held sample and CMBS sample– sample is larger than the median of all borrowers' loan shares. *MktBigBorrower* has value of 1 if a borrower's loan share in each sample is larger than the median of all borrowers' loan shares in each sample. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)
Renegotiation	LnLoanSize	0.682***	0.628***
		(0.174)	(0.175)
	LessDistState	-0.0585	-0.110
		(0.356)	(0.358)
	LessDistState*LnLoanSize	0.166	0.179
		(0.124)	(0.124)
	BigBorrower	1.894***	
		(0.437)	
	BigBorrower*LnLoanSize	-0.465**	
		(0.186)	
	MktBigBorrower		1.906***
			(0.436)
	MktBigBorrower*LnLoanSize		-0.436**
			(0.187)
	Judicial	-0.0255	-0.0226
		(0.154)	(0.154)
	LoanAge	-0.0160***	-0.0161***
		(0.00284)	(0.00286)
	DistBorrower	-0.627	-0.630
		(0.549)	(0.549)
	Constant	-1.606***	-1.507***
		(0.404)	(0.400)
	N	1190	1190
	pseudo R^2	0.1222	0.1253

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Bank-held Sample, Binary Logit: Big Borrowers and Their Regional Concentrations

This table shows, in the bank-held sample, the relation of renegotiation decisions, sizes of borrowers in the market, and their regional concentration level, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *MktBigBorrower* has value of 1 if a borrower's loan share in each sample is larger than the median of all borrowers' loan shares in each sample. *ConcBorrower_Loan (_State, _Mkt, _SubMkt)* has value of 1 if the Herfindhal measure of loan share, i.e., the summation of squared loan (in each states, markets, submarkets, respectively) shares in each borrower's total problem loans in each sample, is larger than the median of each sample. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)	(4)
Renegotiation	LnLoanSize	-0.0778	-0.0908	-0.0825	-0.00990
		(0.129)	(0.125)	(0.125)	(0.130)
	LessDistState	-1.576*	-1.502*	-1.529*	-1.572*
		(0.809)	(0.835)	(0.828)	(0.842)
	LessDistState*LnLoanSize	1.009***	0.972***	0.995***	1.000***
		(0.321)	(0.334)	(0.331)	(0.334)
	MktBigBorrower	15.45***	17.11***	16.05***	16.16***
		(0.492)	(0.845)	(0.821)	(0.699)
	ConcBorrower_Loan	14.02***			
		(0.444)			
	MktBigBorrower*ConcBorrower_Loan	-13.97***			
		(0.631)			
	ConcBorrower_State		14.94***		
			(0.793)		
	MktBigBorrower*ConcBorrower_State		-15.95***		
			(0.915)		
	ConcBorrower_Market			14.10***	
				(0.770)	
	MktBigBorrower*ConcBorrower_Market			-14.88***	
				(0.870)	
	ConcBorrower_Submarket				14.44***
					(0.688)
	MktBigBorrower*ConcBorrower_Submarket				-15.20***
					(0.825)
	Judicial	0.541*	0.645**	0.559**	0.502*
		(0.277)	(0.269)	(0.268)	(0.273)
	LoanAge	-0.0939***	-0.0940***	-0.0943***	-0.0934***
		(0.0106)	(0.0108)	(0.0108)	(0.0107)
	DistBorrower	-13.40***	-14.26***	-13.49***	-14.10***
		(0.481)	(0.496)	(0.487)	(0.481)
	Constant	-14.28***	-15.26***	-14.40***	-14.83***
		(0.471)	(0.798)	(0.793)	(0.704)
N		1093	1093	1093	1093
pseudo R^2		0.4600	0.4624	0.4601	0.4602

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: CMBS Sample, Binary Logit: Big Borrowers and Their Regional Concentrations

This table shows, in the CMBS sample, the relation of renegotiation decisions, sizes of borrowers in the market, and their regional concentration level, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *MktBigBorrower* has value of 1 if a borrower's loan share in each sample is larger than the median of all borrowers' loan shares in each sample. *ConcBorrower_Loan (_State, _Mkt, _SubMkt)* has value of 1 if the Herfindhal measure of loan share, i.e., the summation of squared loan (in each states, markets, submarkets, respectively) shares in each borrower's total problem loans in each sample, is larger than the median of each sample. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)	(4)
Renegotiation	LnLoanSize	0.396***	0.341***	0.418***	0.428***
		(0.0883)	(0.0871)	(0.0893)	(0.0934)
	LessDistState	-0.00740	0.162	0.356	0.336
		(0.380)	(0.355)	(0.362)	(0.370)
	LessDistState*LnLoanSize	0.111	0.0484	-0.0151	-0.0366
		(0.134)	(0.125)	(0.128)	(0.131)
	MktBigBorrower	0.691	0.974*	2.009*	-0.0359
		(0.475)	(0.565)	(1.072)	(0.510)
	ConcBorrower_Loan	-1.033**			
		(0.475)			
	MktBigBorrower*ConcBorrower_Loan	-0.406			
		(0.501)			
	ConcBorrower_State		-0.646		
			(0.563)		
	MktBigBorrower*ConcBorrower_State		-0.499		
			(0.587)		
	ConcBorrower_Market			0.292	
				(1.071)	
	MktBigBorrower*ConcBorrower_Market			-1.745	
				(1.086)	
	ConcBorrower_Submarket				-1.992***
					(0.506)
	MktBigBorrower*ConcBorrower_Submarket				0.265
					(0.538)
	Judicial	0.127	0.0321	0.0445	0.0105
		(0.158)	(0.158)	(0.159)	(0.160)
	LoanAge	-0.0170***	-0.0179***	-0.0187***	-0.0194***
		(0.00299)	(0.00299)	(0.00304)	(0.00316)
	DistBorrower	-1.038**	-0.385	-0.333	-0.285
		(0.437)	(0.507)	(0.502)	(0.489)
	Constant	0.0161	-0.223	-1.280	1.012*
		(0.570)	(0.636)	(1.115)	(0.592)
N		1190	1190	1190	1190
pseudo R^2		0.1663	0.1520	0.1682	0.1878

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Bank-held Sample, Binary Logit: Geographical Diversification

This table shows, in the bank-held sample, the relation of renegotiation decisions and geographical diversification of problem loan portfolios, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in \$millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *ManyLoanPf* has value of 1 if a bank's (special servicer's) loan portfolio has more loans than the median number of loans per bank (special servicer) –the median is 3 for the bank-held sample and 28 for the CMBS sample–. *ConcPf_Loan (_State, _Mkt, _SubMkt)* has value of 1 if the Herfindhal measure of loan shares, i.e., the summation of squared loan (state, market, submarket, respectively) shares in each bank's (special servicer's) total problem loan portfolio, is larger than the median of each sample. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)	(4)	(5)
Renegotiation	LnLoanSize	0.709***	0.0460	-0.0399	-0.000483	0.0231
		(0.214)	(0.133)	(0.131)	(0.130)	(0.127)
	LessDistState	-2.386**	-2.062**	-2.228**	-2.133**	-2.109**
		(0.937)	(0.879)	(0.890)	(0.878)	(0.876)
	LessDistState*LnLoanSize	1.302***	1.214***	1.277***	1.239***	1.228***
		(0.364)	(0.342)	(0.349)	(0.341)	(0.341)
	ManyLoanPf	0.532				
		(0.526)				
	ManyLoanPf*LnLoanSize	-0.626***				
		(0.237)				
	ConcPf_Loan		-0.954**			
			(0.481)			
	ConcPf_Loan*LnLoanSize		0.511**			
			(0.209)			
	ConcPf_State			-1.247***		
				(0.482)		
	ConcPf_State*LnLoanSize			0.640***		
				(0.210)		
	ConcPf_Mkt				-1.100**	
					(0.471)	
	ConcPf_Mkt*LnLoanSize				0.561***	
					(0.205)	
	ConcPf_SubMkt					-1.002**
						(0.476)
	ConcPf_SubMkt*LnLoanSize					0.537***
						(0.206)
	Judicial	0.703***	0.670**	0.599**	0.637**	0.652**
		(0.270)	(0.270)	(0.269)	(0.265)	(0.270)
	LoanAge	-0.103***	-0.0992***	-0.101***	-0.0999***	-0.0996***
		(0.0110)	(0.0111)	(0.0115)	(0.0114)	(0.0112)
	DistBorrower	-12.96***	-11.54***	-11.98***	-13.61***	-13.59***
		(0.518)	(0.730)	(0.714)	(0.733)	(0.726)
	Constant	-0.651	0.141	0.428	0.298	0.215
		(0.423)	(0.389)	(0.411)	(0.399)	(0.395)
	N	1109	939	939	939	939
	pseudo R^2	0.4482	0.4446	0.4494	0.4465	0.4457

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: CMBS Sample, Binary Logit: Geographical Diversification

This table shows, in the CMBS sample, the relation of renegotiation decisions and geographical diversification of problem loan portfolios, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *ManyLoanPf* has value of 1 if a bank's (special servicer's) loan portfolio has more loans than the median number of loans per bank (special servicer) –the median is 3 for the bank-held sample and 28 for the CMBS sample–. *ConcPf_Loan (_State, _Mkt, _SubMkt)* has value of 1 if the Herfindhal measure of loan shares, i.e., the summation of squared loan (state, market, submarket, respectively) shares in each bank's (special servicer's) total problem loan portfolio, is larger than the median of each sample. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)	(4)	(5)
Renegotiation	LnLoanSize	-0.506	0.338***	0.418***	0.350***	0.418***
		(0.364)	(0.0784)	(0.0813)	(0.0918)	(0.0813)
	LessDistState	0.249	0.270	0.202	0.258	0.202
		(0.277)	(0.279)	(0.281)	(0.279)	(0.281)
	LessDistState*LnLoanSize	0.0451	0.0210	0.0466	0.0303	0.0466
		(0.104)	(0.106)	(0.107)	(0.106)	(0.107)
	ManyLoanPf	-3.646***				
		(1.315)				
	ManyLoanPf*LnLoanSize	0.869**				
		(0.361)				
	ConcPf_Loan		0.0389			
			(0.281)			
	ConcPf_Loan*LnLoanSize		0.105			
			(0.111)			
	ConcPf_State			0.440		
				(0.275)		
	ConcPf_State*LnLoanSize			-0.140		
				(0.104)		
	ConcPf_Mkt				-0.0322	
					(0.279)	
	ConcPf_Mkt*LnLoanSize				0.0137	
					(0.106)	
	ConcPf_SubMkt					0.440
						(0.275)
	ConcPf_SubMkt*LnLoanSize					-0.140
						(0.104)
	Judicial	-0.0419	-0.0402	-0.0349	-0.0375	-0.0349
		(0.127)	(0.127)	(0.127)	(0.127)	(0.127)
	LoanAge	-0.0220***	-0.0220***	-0.0218***	-0.0215***	-0.0218***
		(0.00201)	(0.00205)	(0.00203)	(0.00203)	(0.00203)
	DistBorrower	-1.602***	-1.503***	-1.585***	-1.559***	-1.585***
		(0.426)	(0.429)	(0.423)	(0.426)	(0.423)
	Constant	3.803***	0.142	-0.00399	0.188	-0.00399
		(1.330)	(0.232)	(0.230)	(0.264)	(0.230)
	N	1690	1685	1685	1685	1685
	pseudo R^2	0.0991	0.0981	0.0962	0.0949	0.0962

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Bank-held Sample, Binary Logit: Geographical Diversification and Negative Spillovers

This table shows, in the bank-held sample, the relation of renegotiation decisions, geographical diversification of problem loan portfolios, and negative spillover, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *ManyLoanPf* has value of 1 if a bank's (special servicer's) loan portfolio has more loans than the median number of loans per bank (special servicer) –the median is 3 for the bank-held sample and 28 for the CMBS sample–. *ConcPf_SubMkt* has value of 1 if the Herfindhal measure of loan shares, i.e., the summation of squared submarket shares in each bank's (special servicer's) total problem loan portfolio, is larger than the median of the sample. *ImpactOnSubMkt* is the relative size of a loan normalized by the summation of the bank's (special servicer's) all loans in the respective submarket, assuming that the price impact, i.e., the negative spillover, is strongest in the closest region. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)	(4)	(5)	(6)
Renegotiation	LnLoanSize	0.251**	0.262*	0.323***	0.323**	0.255*	0.255
		(0.108)	(0.151)	(0.123)	(0.140)	(0.144)	(0.161)
	LessDistState	-2.168**	-2.121**	-1.945**	-1.945**	-1.895**	-1.895**
		(0.899)	(0.989)	(0.876)	(0.941)	(0.883)	(0.941)
	LessDistState*LnLoanSize	1.229***	1.210***	1.154***	1.154***	1.137***	1.137***
		(0.355)	(0.390)	(0.344)	(0.363)	(0.346)	(0.361)
	ConcPf_SubMkt			-1.172**	-1.172*	-0.890	-0.890
				(0.548)	(0.651)	(0.645)	(0.763)
	ImpactOnSubMkt			-1.009**	-1.009*	-0.891**	-0.891
				(0.431)	(0.580)	(0.452)	(0.606)
	ConcPf_SubMkt*ImpactOnSubMkt			1.595**	1.595**	1.574**	1.574**
				(0.645)	(0.756)	(0.671)	(0.776)
	LnTrbPf					0.105	0.105
						(0.117)	(0.129)
	Judicial	0.656**	0.674*	0.648**	0.648**	0.660**	0.660**
		(0.255)	(0.354)	(0.271)	(0.321)	(0.267)	(0.320)
	LoanAge	-0.0988***	-0.0971***	-0.0962***	-0.0962***	-0.0961***	-0.0961***
		(0.0106)	(0.0132)	(0.0107)	(0.0126)	(0.0106)	(0.0125)
	DistBorrower	-13.77***	-13.30***	-13.35***	-13.35***	-12.70***	-12.70***
		(0.501)	(0.731)	(0.706)	(0.722)	(0.716)	(0.712)
	Constant	-0.352	-0.276	0.254	0.254	-0.303	-0.303
		(0.300)	(0.414)	(0.377)	(0.578)	(0.700)	(0.872)
	N	1109	939	939	939	939	939
	pseudo R^2	0.4299	0.4357	0.4434	0.4434	0.4445	0.4445

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: CMBS Sample, Binary Logit: Geographical Diversification and Negative Spillovers

This table shows, in the CMBS sample, the relation of renegotiation decisions, geographical diversification of problem loan portfolios, and negative spillover, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *ManyLoanPf* has value of 1 if a bank's (special servicer's) loan portfolio has more loans than the median number of loans per bank (special servicer) –the median is 3 for the bank-held sample and 28 for the CMBS sample–. *ConcPf_SubMkt* has value of 1 if the Herfindhal measure of loan shares, i.e., the summation of squared submarket shares in each bank's (special servicer's) total problem loan portfolio, is larger than the median of the sample. *ImpactOnSubMkt* is the relative size of a loan normalized by the summation of the bank's (special servicer's) all loans in the respective submarket, assuming that the price impact, i.e., the negative spillover, is strongest in the closest region. Standard errors are clustered at the property level.

Base outcome: Foreclosure		(1)	(2)	(3)	(4)	(5)	(6)
Renegotiation	LnLoanSize	0.361***	0.358***	0.272***	0.272***	0.331***	0.331***
		(0.0673)	(0.0672)	(0.0704)	(0.0665)	(0.0712)	(0.0609)
	LessDistState	0.277	0.257	0.151	0.151	0.243	0.243
		(0.278)	(0.374)	(0.280)	(0.353)	(0.283)	(0.351)
	LessDistState*LnLoanSize	0.0266	0.0302	0.0428	0.0428	0.0148	0.0148
		(0.106)	(0.0990)	(0.107)	(0.100)	(0.108)	(0.101)
	ConcPf_SubMkt			-0.301*	-0.301	-0.482***	-0.482**
				(0.176)	(0.294)	(0.183)	(0.225)
	ImpactOnSubMkt			0.538**	0.538**	0.405*	0.405*
				(0.235)	(0.213)	(0.239)	(0.235)
	ConcPf_SubMkt*ImpactOnSubMkt			0.629*	0.629**	0.267	0.267
				(0.322)	(0.295)	(0.330)	(0.341)
	LnTrbPf					-0.372***	-0.372***
						(0.0804)	(0.137)
	Judicial	-0.0449	-0.0373	-0.0493	-0.0493	-0.0384	-0.0384
		(0.127)	(0.145)	(0.128)	(0.147)	(0.129)	(0.147)
	LoanAge	-0.0213***	-0.0215***	-0.0216***	-0.0216***	-0.0230***	-0.0230***
		(0.00201)	(0.00446)	(0.00204)	(0.00471)	(0.00211)	(0.00488)
	DistBorrower	-1.568***	-1.565*	-1.447***	-1.447*	-1.531***	-1.531*
		(0.426)	(0.837)	(0.429)	(0.808)	(0.416)	(0.788)
	Constant	0.148	0.168	0.186	0.186	3.750***	3.750**
		(0.200)	(0.383)	(0.206)	(0.396)	(0.806)	(1.601)
	N	1690	1685	1685	1685	1685	1685
	pseudo R^2	0.0949	0.0948	0.1101	0.1101	0.1212	0.1212

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table A.1: Commercial Bank-held Sample, Binary Logit: Renegotiation Size Sensitivity in High ROA Banks, Demeaned Logit and Linear Probability Models

In this table, I test the relation of a loan's size and a renegotiation decision and how the relation interacts with the bank's ROA level, using binary logit models and linear probability models. I also show the results of demeaned tests. For demeaned tests, they are centered at the mean value of *LnLoanSize*. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. In this sample, I can control for more specific characteristics of banks. *LnLoanSize* is ln(loan size in $millions). *HighROA* is an indicator variable of value 1 if a bank's ROA is above the median, 0 if below median. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is the age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *LnBankSize* is ln(Total Assets in $000). *LLA* is the ratio of loan loss allowance/total loan. *DEF* is the ratio of problem loan/total loan measured as (delinquent loan + non accruing loan)/total loan. *RED* is the fraction of real estate problem loan in the problem loan measured as (real estate delinquent loan + real estate non accruing loan)/(delinquent loan + non accruing loan). All variables using accounting information is at the closest quarter-end value right before the resolution decision. Standard errors are clustered at the property level.

		Logit	Logit	LPM	LPM
Base outcome: Foreclosure		Not Centered	Centered at Mean(LnLoanSize)	Not Centered	Centered at Mean(LnLoanSize)
Renegotiation	LnLoanSize	-2.343**	-2.343**	-0.0804**	-0.0804**
		(1.118)	(1.118)	(0.0347)	(0.0347)
	HighROA	-1.291	6.802***	-0.161**	-0.00344
		(2.023)	(1.931)	(0.0722)	(0.0607)
	HighROA*LnLoanSize	6.612***	6.612***	0.128***	0.128***
		(1.489)	(1.489)	(0.0450)	(0.0450)
	Judicial	0.450	0.450	0.123	0.123
		(1.133)	(1.133)	(0.0759)	(0.0759)
	DistBorrower	16.93***	16.93***	-0.0768	-0.0768
		(5.974)	(5.974)	(0.0845)	(0.0845)
	LoanAge	-0.557***	-0.557***	-0.00723***	-0.00723***
		(0.0823)	(0.0823)	(0.00149)	(0.00149)
	LnBankSize	4.252***	4.252***	0.0591***	0.0591***
		(0.685)	(0.685)	(0.0224)	(0.0224)
	LLA	28.67	28.67	-2.078	-2.078
		(26.68)	(26.68)	(1.376)	(1.376)
	DEF	-31.89	-31.89	-0.360	-0.360
		(22.88)	(22.88)	(0.483)	(0.483)
	RED	8.340***	8.340***	-0.197	-0.197
		(2.661)	(2.661)	(0.209)	(0.209)
	Constant	-59.97***	-62.84***	-0.0757	-0.174
		(10.26)	(10.33)	(0.344)	(0.336)
	N	130	130	130	130
	pseudo R^2	0.9149	0.9149	0.5241	0.5241

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Commercial Bank-held Sample, Binary Logit: Renegotiation Size Sensitivity in High LLA Banks

In this table, I test the relation of a loan's size and a renegotiation decision and how the relation interacts with the bank's LLA level, using a binary logit model. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. In this sample, I can control for more specific characteristics of banks. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *HighLLA* is an indicator variable of value 1 if a bank's LLA (the ratio of loan loss allowance/total loan) is above the median, 0 if below median. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is the age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. *LnBankSize* is ln(Total Assets in $000). *DEF* is the ratio of problem loan/total loan measured as (delinquent loan + non accruing loan)/total loan. *RED* is the fraction of real estate problem loan in the problem loan measured as (real estate delinquent loan + real estate non accruing loan)/(delinquent loan + non accruing loan). All variables using accounting information is at the closest quarter-end value right before the resolution decision. Standard errors are clustered at the property level.

		Logit	Logit
Base outcome: Foreclosure		Not Centered	Centered at Mean(LnLoanSize)
Renegotiation	LnLoanSize	-1.083***	-1.083***
		(0.378)	(0.378)
	HighLLA	-1.199	2.331***
		(1.478)	(0.795)
	HighLLA*LnLoanSize	2.884***	2.884***
		(1.035)	(1.035)
	LessDistState	-6.947***	0.106
		(2.548)	(1.126)
	LessDistState*LnLoanSize	5.762***	5.762***
		(1.597)	(1.597)
	Judicial	-2.321**	-2.321**
		(1.115)	(1.115)
	DistBorrower	11.18	11.18
		(7.441)	(7.441)
	LoanAge	-0.417***	-0.417***
		(0.0982)	(0.0982)
	LnBankSize	2.800***	2.800***
		(0.606)	(0.606)
	DEF	-41.61**	-41.61**
		(16.16)	(16.16)
	RED	5.044**	5.044**
		(2.034)	(2.034)
	Constant	-35.70***	-37.02***
		(8.365)	(8.512)
	N	129	129
	pseudo R^2	0.8923	0.8923

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Bank-held Sample: Demeaned Logit and Linear Probability Models

This table shows, in the bank-held sample, the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a binary logit model and linear probability model. I also show the results of demeaned tests. For demeaned tests, they are centered at the mean value of *LnLoanSize*. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. Standard errors are clustered at the property level.

		Logit	Logit	LPM	LPM
Base outcome: Foreclosure		Not Centered	Centered at Mean(LnLoanSize)	Not Centered	Centered at Mean(LnLoanSize)
Renegotiation	LnLoanSize	0.251**	0.251**	0.0161*	0.0161*
		(0.108)	(0.108)	(0.00870)	(0.00870)
	LessDistState	-2.168**	0.00464	-0.126***	0.0647**
		(0.899)	(0.405)	(0.0471)	(0.0288)
	LessDistState*LnLoanSize	1.229***	1.229***	0.108***	0.108***
		(0.355)	(0.355)	(0.0274)	(0.0274)
	Judicial	0.656**	0.656**	0.0401*	0.0401*
		(0.255)	(0.255)	(0.0237)	(0.0237)
	LoanAge	-0.0988***	-0.0988***	-0.00444***	-0.00444***
		(0.0106)	(0.0106)	(0.000459)	(0.000459)
	DistBorrower	-13.77***	-13.77***	-0.0696	-0.0696
		(0.501)	(0.501)	(0.0460)	(0.0460)
	Constant	-0.352	0.0917	0.249***	0.277***
		(0.300)	(0.225)	(0.0292)	(0.0258)
	N	1109	1109	1109	1109
	(pseudo) R^2	0.4299	0.4299	0.2120	0.2120

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: CMBS Sample: Demeaned Logit and Linear Probability Models

This table shows, in the CMBS sample, the relation of a loan's size and a renegotiation decision and how the relation interacts with the distressed level of the region, using a binary logit model and linear probability model. I also show the results of demeaned tests. For demeaned tests, they are centered at the mean value of *LnLoanSize*. There are two possible resolution outcomes-foreclosure or renegotiation- and the base outcome in the test is foreclosure. *LnLoanSize* is ln(loan size in $millions). *LessDistState* is an indicator variable with value 0 if the property is located in AZ, CA, FL, GA, IL, NV, NY, TX, and 1 otherwise. *Judicial* is an indicator variable with value 1 if the state is a judicial state where a foreclosure has to go through court. *LoanAge* is age of a loan measured as the number of months passed since the origination of the loan. *DistBorrower* is an indicator variable with value 1 if it is specified in the data that the borrower of the loan is financially distressed. Standard errors are clustered at the property level.

		Logit	Logit	LPM	LPM
Base outcome: Foreclosure		Not Centered	Centered at Mean(LnLoanSize)	Not Centered	Centered at Mean(LnLoanSize)
Renegotiation	LnLoanSize	0.361***	0.361***	0.0801***	0.0801***
		(0.0673)	(0.0673)	(0.0142)	(0.0142)
	LessDistState	0.277	0.331***	0.0693	0.0752***
		(0.278)	(0.120)	(0.0581)	(0.0266)
	LessDistState*LnLoanSize	0.0266	0.0266	0.00286	0.00286
		(0.106)	(0.106)	(0.0212)	(0.0212)
	Judicial	-0.0449	-0.0449	-0.00821	-0.00821
		(0.127)	(0.127)	(0.0278)	(0.0278)
	LoanAge	-0.0213***	-0.0213***	-0.00452***	-0.00452***
		(0.00201)	(0.00201)	(0.000349)	(0.000349)
	DistBorrower	-1.568***	-1.568***	-0.300***	-0.300***
		(0.426)	(0.426)	(0.0636)	(0.0636)
	Constant	0.148	0.884***	0.522***	0.685***
		(0.200)	(0.127)	(0.0435)	(0.0260)
	N	1690	1690	1690	1690
	(pseudo) R^2	0.0949	0.0949	0.1217	0.1217

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Bibliography

[1] Adelino, Manuel, Kristopher Gerardi, and Paul Willen, 2009, Why don't lenders renegotiate more home mortgages? Redefaults, self-cures and securitization, NBER working paper series working paper 15159.

[2] Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, and Douglas D. Evanoff, 2011, The Role of Securitization in Mortgage Renegotiation, Journal of Financial Economics 102, 559-578.

[3] Ahmed, A. S., C. Takeda, and S. Thomas, 1999, Bank loan loss provisions: A reexamination of capital management, earnings management and signaling effects, Journal of Accounting & Economics 28, 1-25.

[4] Asquith, Paul, Robert Gertner, and David Scharfstein, 1994, Anatomy of financial distress: An examination of junk-bond issuers, The Quarterly Journal of Economics.

[5] Bharath, Sreedhar T., Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan, 2011, Lending relationships and loan contract terms, Review of Financial Studies 24 (4): 1141-1203.

[6] Beatty, Anne., S. L. Chamberlain, and J. Magliolo, 1995, Managing financial reports of commercial-banks: the influence of taxes, regulatory capital, and earnings, Journal of Accounting Research 33, 231-261.

[7] Beatty, Anne and Scott Liao, 2011, Do delays in expected loss recognition affect banks' willingness to lend?, Journal of Accounting & Economics 52, 1-20.

[8] Bergstresser, Daniel, and Thomas Philippon, 2006, CEO Incentives and Earnings Management, Journal of Financial Economics 80, 511-529.

[9] Brown, David T., Brian A. Ciochetti, and Timothy J. Riddiough, 2006, Theory and Evidence on the Resolution of Financial Distress, Review of Financial Studies 19, 1357-1397.

[10] Burgstahler, David, and Ilia Dichev, 1997, Earnings management to avoid earnings decreases and losses, Journal of Accounting and Economics 24, 99-126.

[11] Bushman, Robert M., and Christopher D. Williams, 2012, Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking, Journal of Accounting and Economics 54, 1-18.

[12] Docking, Dian Scott, Mark Hirschey, and Elaine Jones, 1997, Information and contagion effects of bank loan-loss reserve announcements, Journal of Financial economics 43, 219-239.

[13] Financial Accounting Standards Board, 1975, Accounting for contingencies, Statement of Financial Accounting Standards No.5.

[14] Financial Accounting Standards Board, 1977, Accounting by debtors and creditors for troubled debt restructurings, Statement of Financial Accounting Standards No.15.

[15] Financial Accounting Standards Board, 1993, Accounting by creditors for impairment of a loan, Statement of Financial Accounting Standards No.114.

[16] Fonseca, Ana Rosa, and Francisco Gonzalez, Cross-country determinants of bank income smoothing by managing loan loss provisions, Working paper.

[17] Furlong, Fred, and Zena Knight, 2010, Loss provisions and bank charge-offs in the financial crisis: Lesson learned, The Federal Reserve Bank of San Francisco.

[18] Graham, John R., Campbell R. Harvey, and Shiva Rajgopal, 2005, The Economic Implications of Corporate Financial Reporting, Journal of Accounting and Economics 3-73.

[19] Grenadier, Steven, Andrey Malenko, and Ilya A. Strebulaev, 2012, Investment Busts, Reputation, And The Temptation to Blend In With The Crowd, NBER Working Paper.

[20] Hart, Oliver, and John Moore, 1998, Default and renegotiation: A dynamic model of debt, Quarterly Journal of Economics 113, 41.

[21] Healy, Paul, and James M. Wahlen, 1998, A review of the earnings management literature and its implications for standard setting, Working paper.

[22] Hirshleifer, David, and Siew Hong Teoh, 2003, Limited Attention, Information Disclosure, and Financial Reporting, Journal of Accounting and Economics 36, 337-386.

[23] Kanagaretnam, Kiridaran, Gerald J. Lobo, and Robert Mathieu, 2003, Managerial incentives for income smoothing through bank loan loss provisions, Review of Quantitative Finance and Accounting 20, 63-80.

[24] Kothari, S. P., Susan Shu, and Peter D. Wysocki, 2009, Do Managers Withhold Bad News?, Journal of Accounting Research 47, 1:241-276.

[25] Laeven, Luc, and Giovanni Majnoni, 2003, Loan Loss Provisioning and Economic Slowdowns: Too Much, Too Late?, Journal of Financial Intermediation12, 178-197.

[26] Lawrence, Edward C., and Nasser Arshadi, 1995, A multinomial logit analysis of problem loan resolution choices in banking, Journal of Money Credit and Banking 27, 202-216.

[27] Lee, Kai-yan, 2008, Foreclosure's Price-Depressing Spillover Effects on Local Properties: A Literature Review, Federal Reserve Bank of Boston Community Affairs Discussion Paper 2008-01, 1-11.

[28] Lin, Zhenguo, Eric Rosenblatt, and Vincent W. Yao, 2009, Spillover Effects of Foreclosures on Neighborhood Property Values, Journal of Real Estate Financial Economics 38, 387-407.

[29] Madura, Jeff, and Emilio R. Zarruk, 1992, Information Effects of Loan Portfolio Quality on Bank Value, Journal of Economics and Finance, 27-40.

[30] Melzer, Brian T., 2012, Mortgage Debt Overhang: Reduced Investment by Homeowners with Negative Equity, Working paper.

[31] Milbradt, Konstantin, 2012, Level 3 Assets: Booking Profits and Concealing Losses, Review of Financial Studies 25, 1:55-95.

[32] Miller, Gregory S., 2002, Earnings Performance and Discretionary Disclosure, Journal of Accounting Research 40, 1:173-204.

[33] Modigliani, Franco, and Merton H. Miller, 1958, The cost of capital, corporation finance and the theory of investment, The American Economic Review.

[34] Moody's Investors Service, 2007, Bank Financial Strength Ratings: Global Methodology.

[35] Nagar, Venky, 1999, The Role of the Manager's Human Capital in Discretionary Disclosure, Journal of Accounting Review 37, 167-309.

[36] Ng, Jeffrey, and Tjomme O. Rusticus, Banks' survival during the financial crisis: the role of financial reporting transparency, Working paper.

[37] Ng, Jeffrey, and Sugata Roychowdhury, 2011, Loan loss reserves, regulatory capital, and bank failures: evidence from the recent economic crisis, Working paper.

[38] Nichols, D. Craig, James M. Wahlen, and Matthew M. Wieland, 2009, Publicly traded versus privately held: implications for conditional conservatism in bank accounting, Review of Accounting Studies 14, 88-122.

[39] Petersen, Mitchell A., and Raghuram G. Ragan, 1994, The benefits of lending relationships: Evidence from small business data, Journal of Finance 49:1, 3-37.

[40] Piskorski, Tomasz, Amit Seru, and Vikrant Vig, 2010, Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis, Journal of Financial Ecoomics 97, 369-397.

[41] Prendergast, Canice, and Lars Stole, 1996, Impetuous Youngsters and Jaded Old-Timers: Acquiring a Reputation for Learning, Journal of Political Economy 104, 6: 1105-1134.

[42] Rajan, Raghuram G., 1994, Why Bank Credit Policies Fluctuate: A Theory and Some Evidence, Quarterly Journal of Economics 109, 2: 399-441.

[43] Riddiough, Timothy J., and Steve B. Wyatt, 1994, Strategic default, workout, and commercial mortgage valuation, Journal of Real Estate Finance and Economics 9, 5-22.

[44] Riddiough, Timothy J., and Steve B. Wyatt, 1994, Wimp or tough guy: Sequential default risk and signaling with mortgages, Journal of Real Estate Finance and Economics 9, 299-321.

[45] Rogers, William H., and William Winter, 2009, The Impact of Foreclosures on Neighboring Housing Sales, Journal of Real Estate Research 31 (4), 455-479.

[46] Scharfstein, David S., and Jeremy C. Stein, 1990, Herd Behavior and Investment, American Economic Review 80, 3:465-479.

[47] Schuetz, Jenny, Vicki Been, and Ingrid Gould Ellen, 2009, Neighboring effects of concentrated mortgage foreclosures, Journal of Housing Economics 17, 306-319.

[48] Stein, Jeremy, 1989, Efficient capital markets, inefficient firms: A model of myopic corporate behavior, Quarterly Journal of Economics 655-669.

[49] Tirole, Jean, 2006, The theory of corporate finance, Princeton University Press.

[50] The federal reserve system, division of banking supervision and regulation, 2012, Commercial Bank Examination Manual.

[51] Trueman, Brett, and Sheridan Titman, 1988, An explanation for accounting income smoothing, Journal of Accounting Research 26, 127-139.

[52] Verrecchia, Robert E., 2001, Essays on Disclosure, Journal of Accounting and Economics 32, 97-180.

[53] Wahlen, James M., 1994, The nature of information in commercial bank loan loss disclosures, Accounting Review 69, 455-478.

[54] Wall, Larry D., and Timothy W. Koch, 2000, Bank loan-loss accounting: A review of theoretical and empirical evidence, Federal Reserve Bank of Atlanta 1-19.

[55] Zwiebel, Jeffrey, 1995, Corporate Conservatism and Relative Compensation, Journal of Political Economy 103, 1:1-25.