Originate-to-Distribute Model and the Subprime Mortgage Crisis

Amiyatosh Purnanandam *

April 15, 2009

Abstract

An originate-to-distribute (OTD) model of lending, where the originator of a loan sells it to various third parties, was a popular method of credit and liquidity risk-management by financial institutions before the onset of the subprime mortgage crisis. We show that banks with high involvement in the OTD market during the pre-crisis period originated excessively poor quality mortgages. This result is not explained away by differences in observable borrower quality, geographical location of the property or the cost of capital of high and low OTD banks. Instead, our evidence supports the view that the originating banks did not expend resources in screening their borrowers. The effect of OTD lending on poor mortgage quality is stronger for capital-constrained banks and banks with heavy reliance on non-demandable debt. Overall, we provide evidence that lack of screening incentives coupled with leverage induced risk-taking behavior significantly contributed to the current sub-prime mortgage crisis.

JEL Codes: G11, G12, G13, G14.

Keywords: Sub-prime crisis, originate-to-distribute, screening, bank loans, risk-management, incentives.

---

*Amiyatosh Purnanandam can be reached at Ross School of Business, University of Michigan, Ann Arbor, MI 48109, Phone: (734) 764-6886, E-mail: amiyatos@umich.edu. I thank Sugato Bhattacharya, Uday Rajan and George Pennacchi for extensive discussions and detailed comments on the paper. I want to thank Sreedhar Bharath, Charles Calomiris, Sudheer Chava, Douglas Diamond, Han Kim, Pete Kyle, M.P. Narayanan, Paolo Pasquariello, Amit Seru, Sheridan Titman, and seminar participants at the Board of Governors, Washington D.C. and Loyola College, Chicago for valuable suggestions. Kuncheng Zheng provided excellent research assistance. All remaining errors are mine.

1 Introduction

The recent crisis in the mortgage market is having an enormous impact on the world economy. While the popular press has presented a number of anecdotes and case studies, a body of academic research is fast evolving to understand the precise causes and consequences of this crisis (see Greenlaw et al., 2008; Brunnermeier, 2008). Our study contributes to this growing literature by analyzing the effect of banks' participation in the originate-to-distribute (OTD) method of lending on the crisis. We show that the transfer of credit risk through the OTD channel resulted in the origination of inferior quality mortgages. This effect was predominant among banks with relatively low capital and banks with lesser reliance on demand deposits.

As efficient providers of liquidity to both consumers and firms (Diamond and Dybvig, 1983; Holmstrom and Tirole, 1998; Kashyap, Rajan, and Stein, 2002), as better ex-ante screeners (Leland and Pyle, 1977; Boyd and Prescott, 1986), or as efficient ex-post monitors (Diamond, 1984), banks perform several useful functions to alleviate value relevant frictions in the economy. On the asset side of their balance sheet, they develop considerable expertise in screening and monitoring their borrowers to minimize the costs of adverse selection and moral hazard. It is possible that they are not able to take full advantage of these expertise due to market incompleteness, regulatory reasons, or some other frictions. For example, regulatory capital requirements and frictions in raising external capital might prohibit a bank from lending up to the first best level (Stein, 1998). Financial innovations naturally arise as a market response to these frictions (Tufano, 2003; Allen and Gale, 1994). The originate-to-distribute (OTD) model of lending, where the originator of loans sells them to third parties, emerged as a solution to some of these frictions. This model allows the originating financial institution to achieve better risk sharing with the rest of the economy,[1] economize on the regulatory capital, and achieve better liquidity risk management.[2] Thus, banks can use this model to leverage their comparative advantages in loan origination.

These benefits of the OTD model come at a cost. As the lending practice shifts from the

[1] Allen and Carletti (2006) analyze the conditions under which credit-risk transfer from banking to some other sector leads to risk-sharing benefits. They also argue that under certain conditions, these risk-transfer tools can lead to welfare decreasing outcomes.

[2] See Drucker and Puri (2007) for a survey of different theories behind loan sales.

originate-to-hold to originate-to-distribute model, it begins to interfere with the originating banks' ex-ante screening and ex-post monitoring incentives (Pennacchi, 1988; Gorton and Penacchi, 1995; Parlour and Plantin, 2008). It is this cost of the OTD model that lies at the root of our analysis. By separating the originator of a loan from the bearer of its ultimate default risk, the OTD model can dilute the screening incentives of the originating banks. For example, if the originating bank is unable to credibly communicate the unobservable risk or soft information about a loan to its ultimate buyer, then the bank's incentive to expend resources in screening gets diluted (see Rajan, Seru, and Vig, 2009 and Stein, 2002). Further, if the ultimate buyers are unable to understand the true risks of these loans due to some external frictions, then it is in the interest of the originating banks to lend without efficient (costly) screening. An example of such a friction is the potential rating mistakes made by credit rating agencies, which many investors rely upon.

In this paper, our goal is to understand whether participation in the OTD market resulted in the origination of excessively inferior quality mortgage loans as a result of the poor screening incentives of the originating banks. Our key hypothesis is that banks with aggressive involvement in the OTD market had incentives to issue inferior quality mortgages. This allowed them to benefit from the origination fees without bearing the credit risk of the borrowers. As long as the secondary market for mortgage sale was functioning normally, they were able to easily offload these loans to third parties.[3] When the secondary mortgage market came under pressure in the middle of 2007, banks with high OTD loans were stuck with relatively inferior quality mortgage loans. It can take about two to three quarters from the origination to the sale of these loans in the secondary market (Gordon and D'Silva, 2008). In addition, the originators typically guarantee the loan performance for the first ninety days of the loans (Mishkin, 2008). If banks with high OTD loans in the pre-disruption period were originating loans of inferior quality, then in the immediate post-disruption period such banks are likely to be left with a disproportionately large quantity of poor loans. We use the sudden drop in liquidity in the secondary mortgage market to identify the effect of OTD lending on the mortgage quality.

[3]The mortgage market was functioning normally till the first quarter of 2007. In March 2007, several subprime mortgage lenders filed for bankruptcy, providing some early signals of the oncoming mortgage crisis. The sign of stress in this market became visibly clear by the middle of 2007 (Greenlaw et al., 2008).

We define the period up to the first quarter of 2007 as the pre-disruption period, and later quarters as post-disruption. We first confirm that banks with large quantity of origination in the immediate pre-disruption period were unable to sell their OTD loans in the post-disruption period. In other words, banks were stuck with loans that they had intended to sell in the secondary market. Using a difference-in-difference methodology, we then show that banks with higher OTD participation in the pre-disruption period had significantly higher mortgage chargeoffs and defaults by their borrowers in the immediate post-disruption period. We show that it is the proportion of OTD loans in their mortgage portfolio, not the extent of mortgages made by them, that predicts future defaults of their borrowers. In addition, the mortgage chargeoffs and borrower defaults are higher for those banks that were unable to sell their pre-disruption OTD loans i.e., among the banks that were left with large quantities of undesired mortgage portfolios. These differences are not explained by time-trend in chargeoffs, geographical location of the banks or several other bank characteristics that can potentially influence the credit quality of their mortgage loans.

Overall, these results suggest that OTD loans were of inferior quality and banks that were stuck with these loans in the post-disruption period had disproportionately higher chargeoffs and borrower defaults. These results are consistent with the lax screening incentives of the higher OTD banks. The empirical finding, however, raises two immediate questions: (a) Do OTD loans perform worse because of the lax screening incentives of their originating banks or due to other observable differences in the nature of loans made by the these banks? and (b) Are the OTD loans riskier simply because the high OTD banks have lower cost of capital (see Pennacchi, 1988)? We extend our study in two directions. We first analyze the effect of banks' liability structure on the quality of loans originated by them to better understand the driving forces behind the origination of high risk OTD loans. This study also allows us to rule out some of the competing hypotheses. Second, we use a series of matched sample tests using detailed loan-level data to rule out the two alternative hypotheses more carefully.

We find that the effect of pre-disruption OTD lending on the mortgage default rates is stronger among banks with lower regulatory capital. If banks used the OTD model of lending in response to binding capital constraints, then banks with lower capital base should do no worse than the well-capitalized banks. In fact, it can be argued that low-capitalized banks should have better quality of OTD loans since at the margin these banks have to forego better projects due to the unavailability of capital. Our results go in the opposite direction and suggest the presence of risk-shifting motivation behind the origination of such loans. The evidence of lack of screening by lower-capital banks is consistent with Thakor (1996) and Holmstrom and Tirole (1997).

We also find that the effect of OTD loans on mortgage default is concentrated among banks with a lower dependence on demand deposits. In fact, the OTD loans of banks with large deposit base do not experience higher mortgage defaults in the post-disruption period. These results support the view that the fragility of capital structure works as a governance device for the commercial banks as argued by Calomiris and Kahn (1991), Flannery (1994) and Diamond and Rajan (2001). Our evidence is consistent with the key idea of these papers that demand deposits can limit the excessive risk-taking behavior of banks. In summary, these results suggest that risk-shifting incentive, not regulatory capital constraints, was a key driving force behind the origination of excessively risky OTD loans.[4]

To rule out the alternative hypotheses regarding differences in observable loan characteristics and cost of capital of high and low OTD banks more precisely, we obtain detailed loan-level data from the Home Mortgage Disclosure Act (HMDA) database. We conduct three tests based on matched samples of high and low OTD banks. In the first test, we construct a paired sample of high and low OTD banks that are matched along the dimensions of borrowers' observable default risk, properties' location and the bank's size. We show that our results are stronger in the matched sub-sample. Thus, the effect of OTD lending on the mortgage default rates is not an artifact of observable differences in the borrowers' credit risk or the geographical location of high and low OTD banks.

In the second matched sample test, we construct a sample of high and low OTD banks that are matched not only on observable borrower characteristics and property location, but also on the interest rates that they charge to their high risk borrowers at the time of loan origination. If the high OTD banks screened their borrowers and incorporated the effect of unobservable risk

[4]Since capital structure and demand deposit mix of large banks are generally very different from those of the small banks, we pay careful attention to the effect of bank size in these tests.

factors into the loan pricing, then we should see no difference in the ex-post mortgage default rates of high and low OTD banks in this sub-sample. On the other hand, if the high OTD banks did not screen their borrowers, then we should find higher default rates for mortgages originated by the high OTD banks even in this sub-sample. We show that the high OTD banks under-perform even in this matched sample. The evidence, therefore, supports the lax screening incentive hypothesis.

To further rule out the effect of differences in the cost of capital of high and low OTD banks, we create a matched sample by matching smaller banks having large OTD lending with larger banks having little-to-no OTD lending. Our key assumption is that the smaller banks (average asset size of about $500 million) are unlikely to have a lower cost of capital than the large banks (average asset size of about $7.5 billion); therefore, in this sub-sample the effect of OTD lending on mortgage quality can not be attributed to the lower cost of capital of high OTD banks. Our results are equally strong in this sub-sample. Smaller banks with large OTD portfolio suffered higher default rates than large banks with lower OTD portfolio. It is worth pointing out that the ratio of mortgage loans to total assets is similar across large and small banks in this sub-sample. Thus, the effect that we document is due to variations along the dimension of OTD mortgages as a percentage of total mortgages and not because of differences in the bank's overall involvement in mortgage lending.

HMDA database also allows us to analyze the interest rates charged by high and low OTD banks to their high risk borrowers. Banks are required to report the loan spread charged to their borrowers if it exceeds a given threshold. If a bank screens its borrowers carefully on the unobservable dimensions, then it is more likely to charge different interest rates to observationally similar borrowers. Therefore, we should expect to find a wider distribution of interest rates for the same set of observable characteristics for a bank that screens its borrowers more actively. Based on this idea, we compare the distribution of interest rates charged by the high and low OTD banks and find evidence of tighter distribution for the high OTD banks. The result is consistent with the view that the high OTD banks did not engage in active screening of their borrowers.

Our findings have important implications for the market and regulators. Our key test establishes evidence in support of the incentive problems created by the OTD model of lending. Equally important, we show that the capital position and liability structure of a bank has significant effect on the quality of loans originated by them. From the regulator's viewpoint, these findings suggest that the liability structure of a bank has a significant effect on its risk-taking behavior; therefore these findings can serve as inputs to the optimal capital ratio determination exercise.

Our results have an important implication for the markets as well. We show that the quality of mortgage loans depends on the characteristics of its issuer in a predictable way. From a pure pricing perspective, this suggests that there is important information in the originator's characteristics that can improve the default probability and recovery rate estimates of the borrowers. At a broader level, our study suggests that in an information-sensitive asset market, the issuer's capital position and liability structure have important implications for the pricing of the assets in the secondary market.

Our paper is related to a growing literature in this area with important contributions from Keys, Mukherjee, Seru, and Vig, 2010; Mian and Sufi, 2008; Loutskina and Strahan, 2008; Doms, Furlong, and Krainer, 2007; Mayer and Pence, 2008; Dell'Ariccia, Igan, and Laeven, 2008; Demyanyk and Van Hemert, 2008 and others. There are two unique contributions of our paper. This is the first paper that directly compares the relative performance of loans that are originated to be retained versus loans that are originated to be sold. Second, our bank level analysis allows us to detect bank-specific factors that are related to the origination of poor quality mortgages.

Keys et al. (2010) analyze a large sample of securitized loans. They exploit a discontinuity in the likelihood of securitization at a certain threshold of consumers' credit rating to establish a causal link from the ease of securitization to the default performance of mortgage loans. Mian and Sufi (2008) show that the expansion of mortgage credit to areas with high latent demand of mortgage loans caused large price appreciation followed by higher defaults in these areas. Loutskina and Strahan (2008) argue that inadequate level of information production by the lenders contributed to the housing crisis. Titman and Tsyplakov (2007) analyze incentive problems in the securitization of commercial mortgages and find evidence that poorly performing originators have less incentive to expend resources in evaluating the credit quality of prospective borrowers. Our paper also contributes to the literature on banks' risk-management activities and the effect of loan securitization on their performance (see Cebenoyan and Strahan, 2004; Loutskina, 2006; Loutskina and Strahan 2007; Purnanandam, 2007).

We note that our evidence in support of the *dark side* of these credit-risk hedging tools comes from a period of turmoil in the underlying asset markets. To draw strong policy implications, one has to obviously compare these costs with the potential benefits of risk-management tools (Stulz, 1984; Smith and Stulz, 1985; Froot, Scharfstein, and Stein, 1993; Froot and Stein, 1998). Drucker and Puri (2008) shed light on some benefits of the corporate loan sales market. They show that loan sales benefit the borrowers through increased private debt availability.[5]

The rest of the paper is organized as follows. Section 2 describes the data and provides descriptive statistics. Section 3 presents empirical results relating OTD market participation to mortgage defaults. Section 4 explores the linkages with capital position and liability structure. Section 5 provides the matched sample results. Section 6 studies the foreclosure rates and Section 7 concludes the paper.

2 Data

We use two sources of data for our study: call report database for bank information and HMDA (Home Mortgage Disclosure Act) database for loan details. All FDIC-insured commercial banks are required to file call reports with the regulators on a quarterly basis. These reports contain detailed information on the bank's income statement, balance sheet items, and off-balance sheet activities. The items required to be filed in this report change over time to reflect the changing nature of the banking business. As the mortgage sale and securitization activities grew in the last five years, there have been concomitant improvements in the quality of reporting with respect to these items as well.

Beginning with the third quarter of year 2006, banks started to report two key items regarding their mortgage activities: (a) the origination of 1-4 family residential mortgages during

[5]See also Ashcraft and Santos (2008) for a study on the costs and benefits of credit default swaps and Gande and Saunders (2007) for the effect of secondary loan sales market on the bank-specialness.

the quarter with a purpose to resell in the market, and (b) the extent of 1-4 family residential mortgages actually sold during the quarter. These variables allow us to measure the extent of participation in the OTD market as well as the extent of loans that were actually offloaded by a bank in a given quarter. Both items are provided in schedule RC-P of the call report. This schedule is required to be filed by banks with $1 billion or more in total assets and smaller banks if they exceed $10 million in their mortgage selling activities. The data, in effect, is available for all banks that significantly participate in the OTD market. We provide the details of this data in the Appendix.

We construct our key measure of OTD activity as the ratio of loans originated for resale during the quarter scaled by the beginning of the quarter mortgage loans of the bank. This ratio captures the extent of a bank's participation in the OTD market as a fraction of its overall mortgage portfolio. We measure the extent of selling in the OTD market as the ratio of loans sold during the quarter scaled by the beginning of the quarter mortgage loans.

We obtain two measures of mortgage quality from the call reports: (i) chargeoffs on 1-4 family residential mortgages, and (ii) non-performing assets (NPAs) for this category. We use net chargeoffs (net of recoveries) as the first proxy of loan quality. It measures the immediate effect of mortgage defaults on the bank's profitability. However, chargeoffs maybe subject to the reporting bank's discretion. Mortgage NPAs, on the other hand, are free from this bias and provide a more direct measure of the borrowers' default. Our results remain similar for both these measures of loan quality.

We obtain information on bank's assets, profitability, mortgage loans, liquidity ratio, capital ratios, and several other variables from the call report. As is well known, it is important to construct these items across the quarters in a consistent way since the call report's reporting format changes somewhat over time. Our study spans only seven quarters - from 2006Q3, the first quarter with OTD data available, till 2008Q1. The reporting requirement has been fairly stable over this time period and we check every quarter's format to ensure that our data is consistent over time. We provide detailed information on the variables and construction of key ratios in the Appendix.

We obtain detailed loan-level information from the HMDA database. HMDA was enacted by the Congress in 1975 to improve the reporting requirements in mortgage lending business. This is an annual database that contains loan-by-loan information on borrower quality, applicant's demographic information and interest rate on the loan if it exceeds certain threshold. We match the call report and HMDA database for year 2006 to obtain information on the quality of borrowers and geographical location of loans made by banks during the pre-disruption period.

2.1 Descriptive Statistics

Our sample consists of all banks with available data on mortgage origination for resale from 2006Q3 till 2008Q1. We create a balanced panel of banks, requiring the sample bank to be present in all seven quarters. This filter removes only a few banks and does not change any of our results. We impose this filter because we want to exploit the variation in mortgage default rates of the same bank over time as the mortgage market passed through the period of stress.

We begin the discussion of descriptive statistics with a few bar charts. In Figure 1, we plot the quarterly average of loans originated for resale as a fraction of the bank's outstanding mortgage loans (measured at the beginning of the quarter). This ratio measures the bank's desired level of credit-risk transfer through the OTD model. The ratio averaged just below 30% during 2006Q3 and 2006Q4 and dropped to about 20% in the subsequent quarters. The drop is consistent with the popular belief that the OTD market came under tremendous stress during this period. Figure 2 plots the quarterly average of loans sold scaled by the beginning of the quarter loans outstanding. This measures the extent of credit-risk transfer that the bank was actually able to achieve during the quarter. There is a noticeable decline in the extent of loan sales starting with 2007Q1. As we show later, the decline was especially pronounced in banks that were aggressively participating in the OTD market on or before 2007Q1. Overall, these three graphs establish that the extent of loan origination and loans transferred to other parties came down appreciably over this time period.

Figure 3 plots the average percentage chargeoff on 1-4 family residential mortgage loans scaled by loans outstanding. As expected, the quarterly chargeoffs have increased steadily since 2007Q1. The chargeoffs increased four-fold from 2007Q1 to 2007Q4 - a very significant increase for highly leveraged financial institutions. We find similar increase in the non-performing mortgages as well.

Table 1 provides the descriptive statistics of other key variables used in the study. We winsorize data at 1% from both tails to minimize the effects of outliers. The average bank in our sample has an asset base of $4.8 billion (median $800 million). These numbers show that our sample represents relatively large banks of the economy. This is due to the fact that we require data on OTD mortgage origination and sale to be available to be included in our sample. We provide the distribution of other key variables in the table. These numbers are in line with other studies involving large bank samples.

We provide a graphical preview of our results in Figure 4. We take the average value of OTD ratio for every bank during 2006Q3, 2006Q4, and 2007Q1, i.e., during quarters prior to the serious disruption in this market. We call this variable *preotd*.[6] We classify banks into high or low OTD groups based on whether they fall into the top or bottom 20% of the *preotd* distribution. We track the mortgage chargeoffs of these two groups of banks over quarters and plot them in figure 4. Consistent with our earlier graph on the aggregate chargeoffs, both groups have increasing chargeoffs over time. However, there is a remarkable difference in their slopes. While they both started at similar levels of chargeoff in 2006Q3, the high OTD group's chargeoff increased six-fold by the end of the sample period. The low OTD group, on the other hand, increased its chargeoffs by a much lower factor of two-to-three times. We also plot the fitted difference between the two groups over time. The fitted difference measures the difference in the rate of increase in chargeoffs across the two groups and therefore gives a graphical snapshot of the difference-in-difference estimation results. The fitted difference shows a remarkable linear increase over this time period.

In summary, we find that banks with higher OTD participation before the subprime mortgage crisis increase their chargeoffs significantly more than banks with lower OTD. Are these differences significant after accounting for differences in bank characteristics and the quality of borrowers they face? And why does this difference exist across the two groups? We explore these questions through formal econometric tests in the rest of the paper.

[6] Our results are robust to alternative ways of constructing this variable, for example, by averaging over only 2006Q3 and 2006Q4 or by only taking 2007Q1 value as the measure of *preotd*.

3 Mortgage Performance and OTD

We first establish that there was a significant drop in the extent of mortgages sold in the secondary market in the post-disruption period. We follow this up with our main test that examines the mortgage default rates on OTD loans issued in the pre-disruption period.

3.1 Empirical Design & Identification Strategy

Our key argument is that banks with aggressive involvement in the OTD market had incentives to issue inferior quality mortgages. This allowed them to benefit from the origination fees without bearing the credit risk of the borrowers. When the secondary mortgage market came under pressure in the middle of 2007, banks with high OTD loans were stuck with disproportionately large amounts of inferior-quality mortgage loans. The problem is likely to be further exacerbated since the sellers of the OTD loans typically provide warranties for the first ninety days after the loan sale (Mishkin, 2008). Therefore, we expect abnormally poor performance of the mortgage loans of the high OTD banks in the period immediately following the onset of the crisis.

To test this hypothesis in an idealized experimental setting, we would like to have two randomly selected groups of banks that are identical in every respect except that one group is allowed to issue OTD loans (the treatment group), whereas the other one is not (the control group). In our context, the crucial issue is to have banks that are identical in terms of the pool of borrowers they face. This will allow us to make inferences about the supply side incentive effects without contaminating our tests from the demand side (i.e., differences in borrower characteristics). In the absence of a randomized experiment, we conduct our tests in a difference-in-difference setting that is less susceptible to the omitted variable problem. In later sections, we use a matched sample approach that allows us to more directly control for the differences in borrowers' characteristics and property location.

3.1.1 Extent of Mortgage Resale

If banks are able to sell all their OTD loans immediately after the origination, then their post-disruption chargeoffs and mortgage defaults are going to be limited to the extent of initial period guarantee they have provided for these loans. However, there are time lags of up to two to three quarters between the origination of loans and its sale (Gordon and D'Silva, 2008). This creates considerable warehousing or inventory risk for the banks. In these situations, if the mortgage market experiences a disruption and banks are not able to offload these mortgages, they face significant credit and liquidity risk. Since our test relies upon the banks inability to sell these loans after 2007Q1, we first establish the decline in mortgages sold in the secondary market in the post-disruption period. We estimate the following model:

$$sold_{it} = \beta_0 + \beta_1 after_t + \beta_2 preotd_i + \beta_3 after_t * preotd_i + \sum_{k=1}^{k=K} \beta X_{it} + \epsilon_{it}$$

$sold_{it}$ measures bank i's mortgage sale as a fraction of its total mortgage loans at the beginning of quarter t.[7] As described earlier, $preotd_i$ is a time-invariant variable that measures the extent of bank i's participation in the OTD market prior to the disruption in this market in the middle of 2007. We expect to find positive and significant coefficient on this variable since banks with large OTD loans, almost by construction, are more likely to sell large quantities of these loans in the secondary market. $after_t$ is an indicator variable that equals one for quarters after 2007Q1, and zero otherwise. The coefficient on this variable captures the difference in mortgages sold after and before the crisis. The coefficient on the interaction term $preotd_i * after_t$ is the estimate of interest. This coefficient measures the change in the intensity of loans sold around the disruption period across banks with different degrees of *preotd*.

We control for several bank characteristics denoted by vector X_{it} to account for the effect of bank size, liquidity, maturity gap and the ratio of commercial and industrial loans to total assets. More important, we also include a variable *premortgage* that measures the extent of mortgages made by a bank during the pre-disruption period. This variable is computed as the average of the ratio of mortgage loans to total assets during 2006Q3, 2006Q4, and 2007Q1.

[7] Our results are similar if we add the mortgages originated during the quarter in the denominator.

We include this variable and its interaction with *after* to separate the effect of high mortgage banks from the high OTD banks.[8]

To provide a benchmark specification, we first estimate this model using OLS method. All standard errors are clustered at the bank level. In the OLS model, we include indicator variables for the bank's state to control for state-specific differences in mortgage activities. Results are provided in Model 1 of Table 2. As expected, we find large and positive coefficient on the *preotd* variable. The coefficient on the interaction of *after* and *preotd* is negative and highly significant. In fact the coefficient on *after* dummy by itself is positive and significant. It's within the high *preotd* banks that we see a sharp decline in the extent of loans sold.

We provide bank fixed-effect estimation results in Models 2 and 3 of Table 2. This estimation method is more appealing as it controls for bank-specific unobservable effects and allows us to more precisely estimate the effect of disruption in mortgage market on the high OTD banks. *preotd* and *premortgage* are omitted from this model as they are captured in the bank fixed-effects. Our identification comes from the interaction of *after* with *preotd*. In Model 2, we find significant negative coefficient on this interaction term, which confirms that banks with large OTD loans in the pre-disruption period suffered significant decline in mortgage resale during the post-disruption period. In unreported tests, we estimate this model without the interaction term $after * preotd$ and find significant negative coefficient on *after*. These findings show that the decline in mortgage resale is concentrated among high *preotd* banks. In Model 3, we re-estimate the fixed-effect model after removing banks with more than $10 billion in asset size from the sample. It is often argued that the business model of very large money-centric banks is different from regional and local banks. We find that our results are equally strong after excluding these large banks from the sample.

These results show that banks with higher origination of loans for distribution in the pre-disruption period were stuck with disproportionately higher fraction of these loans on their balance sheet in the post-disruption period. This is consistent with our assertion that the disruption in the mortgage market created warehousing risk for the banks, which in turn led to an accumulation of loans that were intended to be sold by the banks.

[8]Our results are similar without the inclusion of *premortgage* variable in the regression models.

3.2 Mortgage defaults

We now relate the mortgage default rates to the bank's involvement in the OTD market. We estimate the following bank fixed-effect model:

$$performance_{it} = \mu_i + \beta_1 after_t + \beta_2 after_t * preotd_i + \beta_3 * premortgage_i + \sum_{k=1}^{k=K} \beta X_{it} + \epsilon_{it}$$

The dependent variable measures the performance of the mortgage portfolio of bank i in quarter t. We use two measures of performance: net-chargeoffs and non-performing mortgages i.e., mortgages that are in default for more than 30 days. Both these measures are scaled by the beginning of the quarter mortgage loans of the bank. μ_i stands for bank fixed-effects and X is a vector of bank characteristics. The coefficient on the $after$ variable captures the time-trend in performance before and after the mortgage crisis. The coefficient on the interaction term $preotd_i * after_t$ is the estimate of interest. This coefficient measures the change in chargeoffs/NPAs around the crisis period across banks with different intensities of participation in the OTD market prior to the crisis. We include the interaction of $after$ with $premortgage$ to ensure that the relation between OTD loans and mortgage performance is not an artifact of higher involvement in mortgage lending by higher OTD banks.[9]

We control for a host of bank characteristics that can potentially affect the quality of mortgage loans. We control for the bank's size by including the log of total assets in the regression model. We include the ratio of commercial and industrial loans to total assets to control for the broad business mix of the bank. A measure of 12-month maturity gap is included to control for the interest rate risk faced by the banks. Finally, we include the ratio of liquid assets to total assets to control for the liquidity position. The last three variables broadly capture the extent and nature of credit risk, interest rate risk, and liquidity risk faced by the banks.

The identifying assumption in this model is that the average difference in the quality of loans made by banks with different degrees of pre-crisis OTD participation is captured by the fixed-effects, whereas the economy-wide shift in the mortgage quality over the time period is

[9] We re-estimate these models without including the interaction of $after$ and $premortgage$ and obtain similar results.

captured by *after* dummy variable. Under these assumptions, the interaction term identifies the differential effect of OTD participation on the quality of mortgages before and after the crisis. Results are provided in Table 3. We provide results for the entire sample in Models 1 and 2. In Models 3 and 4 we exclude large banks with asset size more than $10 billion from the sample.

We find that the extent of participation in the OTD market during the pre-disruption period has a significant effect on the performance of the bank's mortgage portfolio during the post-disruption period. In the chargeoff regression result of Model 1, we find a positive and significant coefficient of 0.0414 on the $after * preotd$ term. The economic magnitude of this estimate is large since it is almost equal to the average value of chargeoff in our sample. In Model 2 we repeat the analysis with non-performing mortgages as the measure of loan quality. This variable directly measures borrowers' default on their mortgage payments. We find positive and significant coefficient on the interaction term $after * preotd$. These effects are economically large and are not explained away by a bank's size, maturity gap, liquidity risk, geographical area or any other omitted time-invariant bank-specific factor. We repeat our analysis after excluding the large banks from the sample and obtain similar results.

In our next test we model the mortgage defaults as a function of the extent of OTD loans that a bank is stuck with. For every bank in the sample, we create a measure of *stuck* loans in the following manner. We compute the quarterly average of OTD loans originated during the pre-crisis quarters i.e., during the quarters 2006Q3, 2006Q4, and 2007Q1. From this we subtract the quarterly average of loans sold during the post-crisis periods, i.e., during 2007Q2 to 2008Q1. We scale the difference by the bank's average mortgage assets during the pre-crisis quarters. This variable refines the earlier *preotd* measure by subtracting the extent of loans that a bank could actually sell in the post-disruption period. Therefore, this variable allows us to more directly analyze the effect of loans that a bank had originated to distribute but was unable to distribute due to the drop in liquidity in the secondary market.

We re-estimate the $performance$ regression model by replacing *preotd* with *stuck*. Results are presented in Table 4. We find large positive coefficient on the interaction term $preotd * stuck$ in Model 1. In model 2, we run a horse race between $after * preotd$ and $after * stuck$ and find that the effect of OTD loans on mortgage chargeoffs mainly come from the variation in *stuck* variable. In Model 3, we show that our results are robust to the exclusion of large banks. Model 4, 5 and 6 repeat the regressions with mortgage NPA as the measure of performance. All our results remain strong. In fact the economic magnitude of results improve for specification involving $after * stuck$ as compared to the earlier specification. In a nutshell, these results provide more direct evidence that banks that were stuck with OTD loans experienced larger mortgage defaults in the post-disruption period. The results of this section also suggest that the effect that we document are related to the OTD mortgages and not to the overall mortgage portfolio of the banks.

Overall, these results suggest that OTD loans were of inferior quality and banks that were stuck with these loans in the post-disruption period had disproportionately higher chargeoffs and borrower defaults. Though the results are consistent with the lax screening incentives of the higher OTD banks, they raise two immediate questions: (a) Do OTD loans perform worse because of the lax screening incentives of their originating banks or due to other observable differences in the nature of loans made by the these banks? and (b) Are the OTD loans riskier simply because the high OTD banks have a lower cost of capital (see Pennacchi, 1988)? We extend our study in two directions. We first analyze the effect of banks' liability structure on the quality of loans originated by them to better understand the driving forces behind the origination of high risk OTD loans. This study also allows us to rule out some of the competing hypotheses. Second, we use a series of matched sample tests using detailed loan-level data to rule out the above-mentioned alternative hypotheses more carefully.

4 Capital & Liability Structure

Why did banks engage in such behavior? Rajan (2008) argues that incentives of the financial market participants might have been a significant contributing factor to this crisis. The call report database does not provide information on the compensation-based incentives of bank managers, which limits our ability to analyze the effect of incentives on the quality of loans originated by banks. In addition to monetary incentives, however, a bank's liability structure can have a significant impact on its risk-taking behavior. In this section, we investigate the effect of incentives generated from the liability side of a bank's balance sheet on the quality of OTD loans.

4.1 Effect of capital constraints

As discussed earlier, the transfer of credit risk to third parties has several advantages. By de-linking the origination of loans from funding, banks can capitalize on their comparative advantage in loan origination without requiring a large capital base. The benefit can be especially high when banks are capital constrained. Regulatory capital constraints might limit a bank's ability to provide loans to its creditworthy consumers. If banks participated in the OTD market to save regulatory capital, then it is expected that capital-constrained banks should do no worse than other banks in terms of mortgage default rates in the post-disruption period. It can even be argued that the OTD portfolio of such capital-constrained banks should be of better quality since their incentive to participate in this market is more likely to come from sound economic reasons without diluting their screening incentives.

On the other hand, capital-constrained banks can have lower screening and monitoring incentives (Thakor, 1996; Holmstrom and Tirole, 1997). Poorly capitalized banks have higher risk-shifting incentives due to their limited liability (Jensen and Meckling, 1976) as well as the deposit insurance provided by the FDIC.[10] If banks are using the OTD market to create riskier loans by diluting their screening standards, then capital-constrained banks can have a higher incentive to make inferior loans. Thus, we have sharply different predictions about the effect of capital constraints on the extent of mortgage defaults by high *preotd* banks. We estimate a triple-differencing model to test this prediction. An additional advantage of this estimation approach is that it exploits variations within the set of high OTD banks, thereby minimizing the omitted variables concerns present in any double-differencing model. We estimate the following

[10] The deposit insurance channel works only if FDIC subsidizes the insurance premium paid by banks for this service.

model:

$$
\begin{aligned}
performance_{it} &= \mu_i + \beta_1 after_t + \beta_2 after_t * preotd_i + \beta_2 after_t * lowcap_i \\
&+\beta_3 after_t * preotd_i * lowcap_i + \sum_{k=1}^{k=K} \beta X + \epsilon_{it}
\end{aligned}
$$

The dependent variable, $performance_{it}$, is measured by either the mortgage chargeoffs or the non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. *lowcap* is an indicator variable that equals one for banks that fall in the bottom quartile of the total risk based capital ratio, zero otherwise. We take the average value of this ratio for the pre-disruption quarters to capture the effect of capital ratio at the time these loans were made.

Table 5 provides the estimation results. Consistent with our earlier analysis we present results for both "All Bank" sample and "Excluding Large Banks" sub-sample. In Model 1 we use chargeoffs as the performance measure and find a significant positive coefficient on the triple interaction term $after * preotd * lowcap$. The coefficient on $after$*$preotd$ is positive and significant as well, but the point estimate drops to 0.0289 as compared to 0.0414 in the corresponding base model. The coefficient on the triple interaction term is almost 50% higher than the coefficient on the double interaction term. Similar results hold for specification using NPA as the performance measure. In this specification, the interaction term $after$*$preotd$ becomes insignificant by itself. The positive effect of *preotd* on mortgage NPA is entirely captured by the lower capitalization banks.

These results show that the effect of *preotd* loans is mainly concentrated among lower capitalization banks. This shows that banks used the OTD channel mainly to originate poor-quality loans rather than to save on regulatory capital. This result has important implications for the role of capital in a bank's lending and risk-taking decisions.

4.2 Effect of demand deposits

After establishing the role of capital ratios on chargeoffs, we turn our attention to the liability structure of banks. In particular, we focus on the extent of demand deposits in their total deposits. The existence of demand deposits is one of the defining features of the banking industry. A large body of banking research has focused on the presence of demand deposits and its incentive effects on banks. Starting with the seminal work of Diamond and Dybvig (1983), researchers have argued that demand deposits improve social welfare by efficient sharing of liquidity risk faced by the depositors. Calomiris and Kahn (1991) and Flannery (1994) argue that demand deposits can control the risk-taking activities of a bank. Demand depositors can withdraw their money at any time. This fragility of a bank's capital structure can act as a disciplining device by committing the banker to avoid undesirable risky behavior (see Diamond and Rajan, 2001).

Motivated by these arguments, we conjecture that banks with higher fraction of demand deposits are less likely to engage in risk-seeking behavior by originating inferior-quality loans. We adopt the same empirical methodology that we use for test involving the effect of capital ratios. We estimate a triple-differencing model and provide results in Table 6. We measure the extent of dependence on demand deposits by taking the ratio of demand deposits to total liability of the bank. The ratio is computed as the average over the pre-crisis quarters. We create an indicator variable *highdep* that equals one for banks that fall in top quartile of this ratio, zero otherwise. For easier interpretation of our results, we include *lowdep* defined as (1-*highdep*) in the regression model.

We find that among the higher *preotd* banks, the chargeoffs and non-performing mortgages increased by a considerable amount for banks with lower levels of demand deposits in their liabilities. Among the set of high *preotd* banks, the ones that are primarily funded by demand deposits did not originate excessively risk loans as evident by the insignificant coefficient on *after*preotd* interaction variable in this model. Said differently, the effect of poor incentives created by the participation in the OTD market is primarily concentrated within banks that raise most of their capital through non-demandable deposits.

Together these results suggest that banks funded by wholesale term debt (i.e., non-equity and non-demandable debt) were the predominant originators of inferior quality OTD mortgages. The evidence suggests that the bank's risk-taking incentives, and not the incentive to save regulatory capital, has been the key driver behind the origination of excessively risky OTD loans. We now turn to the matched sample analyses that provides further evidence in support of inferior screening incentives of the banks and allows us to rule out some of the important competing hypotheses more directly.

5 Matched sample analysis

We use Home Mortgage Disclosure Act (HMDA) database to obtain information on the characteristics of mortgages made by commercial banks during 2006. HMDA was enacted by the Congress in 1975 to improve disclosure and promote fairness in the mortgage lending market. This is a comprehensive source of loan-level data on mortgages made by commercial banks, credit unions and savings institutions. The database provides detailed information on the property's location, borrower's income, loan amount along with a host of borrower and geographical characteristics on a loan-by-loan basis. We match the bank-level call report data with the loan-level HMDA data using the FDIC and OCC certificate numbers of the commercial banks. With the matched sample of banks and individual loans, we proceed in four steps to rule out several possible alternative hypotheses.

5.1 Differences in observable borrower characteristics

Are our results driven by differences in observable borrower and loan characteristics of high and low OTD banks? Using HMDA database, we construct a matched sample of high and low OTD banks on several observable dimensions to rule out this hypothesis. We divide sample banks into two groups (above and below median) based on their involvement in the OTD market prior to the disruption (i.e., *preotd* variable). Our goal is to match every high OTD bank with a low OTD bank that has made mortgages in similar geographical area to observationally similar borrowers.

We want to match on the geographical location of properties to control for the effect of changes in house prices. This will ensure that our results relating OTD-lending to mortgage quality is not an artifact of differences in decline in house prices across these two groups. We first compute the fraction of loans issued by a given bank in every state and then take the state with the highest fraction as the bank's main state. This method allows us to match on the location of property rather than on the state of incorporation in case they differ. Using the HMDA dataset, we obtain two key measures of the borrower quality: the loan-to-income ratio of the borrowers and the borrower's annual income. We compute the averages of these numbers to construct the average borrower quality of a bank.

Our matching procedure proceeds as follows. We take a high OTD bank (i.e., above median *preotd* bank) and consider all low OTD banks in the same state as potential matching banks. We break banks into three size groups based on their total assets: (i) below \$100 million; (ii) between \$100 million and \$1 billion; and (iii) between \$1 billion and \$10 billion. We do not include banks with asset size more than \$10 billion in this analysis to ensure that our results are not contaminated by very large banks operating across multiple markets.[11] From the set of all low OTD banks in the same state, we consider banks in the same size group as the high OTD bank's size group. We further limit this subset to banks that are within 50% of the high OTD bank in terms of the average income of their borrowers. From this subset, we obtain the bank with the closest average loan-to-income ratio of its borrowers as the high OTD bank as the matched bank. We match without replacement to find a unique matching bank for each high OTD bank.

Our goal is to find pairs of bank that have made mortgages to observationally equivalent borrowers, but with varying intensity of OTD loans. We have conducted several alternative matching criteria by changing the cut-offs for bank size, borrower's income and loan-to-income ratio. Our results are robust. To save space, we provide estimation result for the base model only. Due to the strict matching criteria, our sample size drops for this study. We are able to match 140 high OTD banks using this methodology. Out of the 140 matched banks, in regressions we lose five matched banks due to the non-availability of other data items.

Given the matching criteria, this sample is dominated by regional banks. The average asset size of the banks in this matched sample is \$1.52 billion for the high OTD banks and \$1.50 billion for the low OTD banks. In Figure 5, we plot the distribution of loan-to-income ratio of the high and low OTD banks in the matched sample. Not surprising, the two distributions are almost identical. We also plot the average income in the neighborhood (obtained from

[11]We have estimated the model without this restriction and all results remain similar.

the HMDA database) where the property is located across the two groups of banks. Again we find statistically indistinguishable distribution across the two groups. In unreported analysis, we compare several other characteristics across these two groups and analyze them using Kolmogorov-Smirnov test for the equality of distribution. We find that these two groups are statistically indistinguishable in terms of the following characteristics: borrower's income; loan-to-income ratio; loan amount; loan security; and neighborhood income.

We conduct our tests on the matched sample and report the estimation results in Table 7 of the paper. The matched sample results are stronger than the base case specification presented in Table 3. The coefficient on $after * preotd$ is almost twice as much as the base case. We also estimate the effect of stuck loans and the effect of bank's capital and debt structure on the matched sample. To save space, we only provide estimation results for chargeoff as the performance measure since the results are similar for mortgage NPAs. We find that all results remain robust on this sub-sample. Overall the analysis of this section shows that the variation generated by the OTD model of lending is unlikely to be explained away by differences in borrower's credit risk, property location or bank size.

5.2 Unobservable borrower characteristics

Our results suggest that OTD mortgages performed much worse even after conditioning on observable borrower characteristics. This leads to two possibilities: (a) these loans were different on unobservable dimensions and the originating banks properly priced these unobservable factors to account for the higher risk; or (b) the originating bank didn't expend enough resources in screening these borrowers under the knowledge that these loans will be subsequently sold to third parties. While both of these hypotheses are consistent with the view that OTD loans were riskier, under the first possibility the bank is properly screening these loans and pricing them accordingly.

We create a particular type of matched sample to separate these two hypotheses. By definition, it's impossible for us to directly incorporate the unobservable dimensions of borrowers' risk in our analysis. However, if banks are expending resources in screening the high risk OTD loans, then it should be reflected in the loan pricing. We exploit this idea in the following test.

In addition to property location and borrower's loan-to-income ratio, we now also match on the interest rates charged by the banks at the time of the loan origination. HMDA database reports loan spreads for high risk borrowers only. The reporting requirement stipulates that banks should report loan spreads on all first security loans with a spread of above 3% and all junior security loans with a spread of above 5%. Thus, these loans generally fall in the subprime category. Though we are unable to match on loan spreads for the entire mortgage portfolio, it is this subset that is more meaningful in terms of our economic exercise. We compute the average loan spread on a bank-by-bank basis and match banks based on these averages.

For every high OTD bank, we first find a set of matching low OTD banks that meet the following criteria: (a) it primarily operates in the same state as the high OTD bank; (ii) it is in the same size group; and (iii) it's within 50% of the average loan-to-income ratio of the high OTD bank[12] (all three measures are as defined earlier). From this set, we select the low OTD bank with the closest loan spread as the matched bank.

The resulting matched sample comprises a set of high and low OTD banks that have made mortgages to observationally equivalent borrowers in similar geographical area at similar rates.[13] The extent of mortgage loans (as a fraction of total assets) made by these banks in the pre-disruption period is also statistically indistinguishable. By construction, they differ in terms of the extent of OTD loans made during the pre-disruption period. Thus, this sample exploits the variation along the OTD dimension keeping several observable and the *priced component of unobservable characteristics* constant. If banks screened the OTD loans and incorporated the effect of privately acquired information into the pricing of these loans, then we should not expect to see any difference in the performance of high and low OTD mortgages in this sub-sample. If, on the other hand, riskier loans were made without properly incorporating the effect of unobservable risk in loan pricing, then we are likely to see differences in their performance even on this sub-sample.

Results are provided in Table 8. In Models 1 and 2, we estimate the base case model relating mortgage NPAs and chargeoffs to the extent of OTD loans made during the pre-

[12]Results are unchanged if we narrow this band to 25%.

[13]We compare the distribution of key borrower characteristics for this matched sample also. As expected, we find that the high and low OTD banks in this sample have borrowers with similar loan-to-income ratio, loan security and neighborhood income.

disruption period. We find strong effects of *preotd* on both these measures of mortgage quality. We replicate regressions relating chargeoffs and mortgage NPAs to the stuck loans as well as the banks' capital and debt structure. We present these results with chargeoffs as the measure of loan performance in Models 3, 4 and 5. In unreported tests, we find similar results for the NPA-based analysis. We find strong results for both stuck loans and capital ratio regressions. The effect of demand deposit is in the same direction, but statistically weaker for this sub-sample.

Overall, these results show that even for banks that have charged similar rates and have observationally similar pool of borrowers, the performance of high OTD bank is significantly worse in the post-disruption period. The evidence in not consistent with an economic model in which banks properly screened these borrowers, evaluated their true credit-worthiness for the same set of observable characteristics and charged higher rate for making these loans. On the contrary, the evidence suggests that OTD loans were made without proper screening on unobservable dimensions.

5.3 Cost of capital channel

An important benefit of the OTD model is that it allows the selling bank to lower its cost of capital. Pennacchi (1988) shows that banks can lower their cost of capital by transferring credit risk through loan sales. In a competitive deposits market, loan sales can lower the bank's cost of capital by allowing it to save on regulatory capital and required reserves (see also Gorton and Pennacchi (1995)). If high OTD banks have lower cost of capital, then they can make loans to relatively higher credit risk borrowers since some of these borrowers present positive NPV projects only to the high OTD banks. Therefore, the ex-post performance of the higher OTD banks' mortgage portfolio is likely to be worse in bad economic times due to the presence of these marginal borrowers.

Are our results simply driven by the lower cost of capital of high OTD banks? To rule out this alternative hypothesis, we compare the performance of smaller banks having large OTD portfolios with large banks having little-to-no involvement in the OTD model of lending. Our assumption is that it is unlikely that a bank with $500 million in assets, even after engaging in the OTD model of lending, has lower cost of capital than a bank with $10 billion in assets.

Several empirical studies find a negative link between firm size and its cost of capital. Thus, this test allows us to compare the performance of OTD loans issued by banks with relatively higher cost of capital than the non-OTD banks.

We compute the bank's average assets during the pre-disruption quarters (i.e., 2006Q3, 2006Q4 and 2007Q1) and classify them into small banks if their asset is less than $1 billion. From this set, we obtain banks with higher than median levels of OTD lending during the pre-disruption quarters. For every small bank, we consider all large banks (assets greater than $10 billion) in below median OTD group that have made the largest fraction of mortgages in the same state as the small bank. We require the large bank's borrowers' average income to fall within 50% of the small bank's borrowers. From the resulting set, we select the large bank with closest loan-to-income ratio of borrowers as the matched bank. Given the strict nature of matching, our sample drops for this analysis. We are able to obtain a match for 71 small banks by this method. The average asset size of high OTD banks in this sample is $550 million, whereas the low OTD banks have average asset size of about $7.25 billion.

We re-estimate our models for this sub-sample and present the results in Table 9. Our results remain strong. The high OTD small banks issued significantly lower quality mortgages than the low OTD large banks. The differential effect of OTD loans, therefore, is unlikely to be explained away by the lower cost of capital of high OTD banks.

5.4 Shrinkage in loan spreads

In this section, we provide a more direct evidence of lax screening incentive based on an analysis of the dispersion in loan spreads charged by high and low OTD banks. To motivate the empirical test, consider a setting where two originating banks are faced with similar borrowers based on observable characteristics. Bank S screens the applicants, evaluate its true credit worthiness based on privately observed signals and grants loans at fair price. Bank NS does not screen the borrowers and offers its borrowers a standard rate conditional on observable signals. In this model, the S bank discriminates its borrowers significantly more than the NS bank for the same set of observable characteristic of the borrowers. Therefore, an implication of lax screening is that the loan rate charged by the S bank will have a wider distribution than the loan rate charged by the *NS* bank. Thus, if the high OTD banks are of the *NS* type, then we expect to observe tighter distribution of loan rates for these banks after parsing out the effect of observable signals. This test is motivated by the arguments developed more formally in Rajan, Seru and Vig (2009), who argue that the default prediction models fail in systematic ways as the reliance on hard information in loan approval decisions increases.

Based on this idea, we compare the distribution of loan spreads charged to borrowers across high and low OTD banks. We first obtain all loan-level observation from the HMDA data with non-missing observation on loan spreads. As discussed earlier, this data is reported for the very high risk borrowers only: i.e., for the subset for which the effect of lax screening is potentially higher. We first estimate a model of loan spread to parse out the effect of observable characteristics. We estimate the following model with loan-level data:

$$rate_{ib} = \alpha + \beta X_{ib} + \epsilon_i$$

$rate_{ib}$ is the percentage spread (over comparable maturity treasury security) on mortgage to borrower i by bank b. X_{ib} is a set of borrower, loan, and bank characteristics that are observable and likely to affect the loan rate. We include following borrower characteristics in the model: log of borrower's annual income, log of loan amount, loan-to-income ratio, log of neighborhood median family income reported by HMDA, percentage minority population in the neighborhood, whether the loan is secured by a first lien or not, whether the property is occupied by the owner or not, purpose of the loan (home purchase, improvement or refinancing), loan type (conventional or FHA insured loan), indicator for the state of the property, applicant's sex and race. This is a comprehensive set of characteristics aimed at capturing the borrowers default risk, demographics and other correlated variables. In addition to these factors, we also include the banks' asset size (log of assets), liquidity ratio, maturity gap, CIL loans to total asset ratio and mortgage-loans to total asset ratio. These variables are included to control for bank specific effects in pricing such as the bank's cost of capital and relative advantage in lending mortgage loans.[14]

[14]We have experimented with several other reasonable specifications and obtained similar results. We report results based on one of the most comprehensive models to capture the effect of unobservable information on loan spreads.

We are interested in the dispersion of the residual of this regression, i.e., ϵ_i. Our hypothesis is that the high OTD banks did not expend resources in discriminating across borrowers with similar observable quality, but with different unobservable signals. ϵ_i captures the effect of such unobservable factors. We compute three measures of dispersion namely, the standard deviation, the difference between the 75th and 25th percentiles and the difference between the 90th and 10th percentiles. Results are reported in Table 10. Panel A presents results for all banks, whereas Panel B is for the matched sample used in sub-section 5.1. We find a consistent pattern of shrinkage in loan spreads for the high OTD banks. The standard deviation of loan rates issued by the high OTD banks is about 15-20% lower than the low OTD banks. We observe similar patterns for the other two measures of dispersion. We conduct Bartlett's test for the equality of variance of the two distributions and strongly reject the null hypothesis of equal variance for the two groups. The Kolmogorov-Smirnov test statistic strongly rejects the equality of the two distributions as well.

Overall, we show that the low OTD banks offered loans at more discriminating terms for the same observable characteristics as compared to the high OTD banks. This finding is consistent with the assertion that the high OTD banks did not expend as much resources in screening their borrowers as their low OTD counterparts.

6 Robustness: OTD and Foreclosures

As our final test, we investigate the effect of the participation in the OTD market on the extent of foreclosures on these loans. We want to investigate if a high proportion of OTD loans in the pre-disruption period resulted in higher foreclosures in the post-disruption period. To test this hypothesis, ideally we need data on the extent of foreclosures on pre-disruption OTD loans. Unfortunately, this data is not available to us. As the next best alternative, we explore the extent of foreclosures on non-recourse loans serviced for others by a bank. Banks have been mandated to report this data item in the call reports starting with the second quarter of 2008. For every bank, we have the dollar amount of 1-4 family residential mortgages serviced for others without recourse that are in the process of foreclosure at the end of the second quarter of 2008. Banks might act as a servicer for loans that they originated from the home-owners directly or loans that they bought from other banks to sell them to third parties. In either case, this provides a reasonable proxy for the extent of foreclosure on the OTD loans.

We note two caveats relating to potential measurement errors in this proxy. First, many OTD loans are sold to other parties without servicing obligations, and this measure misses the extent of foreclosure experienced on those loans. Second, if a bank acts merely as a servicer without any role in the origination of the loans, then our proxy can be contaminated.

With these limitations in mind, we relate the extent of OTD participation in the pre-disruption period to the foreclosures on these loans. We scale the foreclosure variable with the bank's outstanding mortgages during the pre-disruption period and use the scaled variable as the dependent variable in the regression model. We estimate the following cross-sectional Tobit model:

$$foreclosure_i \quad = \quad \beta_0 + \beta_1 preotd_i + \beta_2 X_i + \gamma State_i + \epsilon_i$$

Since we do not observe foreclosures on the entire OTD portfolio, we consider the true $foreclosure$ variable as a latent variable. The observed variable is considered left censored at zero, and the model is estimated using a Tobit regression technique. In the model we control for log(total assets), capital position, mortgage to total asset ratio, and liquidity to control for the effects of bank's size and financial strength. We control for state dummies to account for general economic conditions that might influence the extent of foreclosure in a given area. Finally, we include a variable $floatmort$ that captures the nature of mortgages made by banks. This variable is constructed as the ratio of mortgage loans that are due to reprice or mature within a year as a fraction of total mortgages. We include this variable as a control for the effect of interest-rate and refinancing risk on foreclosure decisions.

Results are provided in table 11. In Model 1 we only control for the bank's size, its total mortgage portfolio and state fixed effects. Model 2 uses all the control variables mentioned above. We find that banks with high OTD on or before 2007Q1 have remarkably higher fraction of mortgages under foreclosure in 2008Q2. This evidence is consistent with the rest of the evidence in the paper that OTD loans are of inferior quality. The key advantage of this estimation is that it allows us to directly relate the participation in the OTD model to distressed mortgage loans.

7 Discussion & Conclusion

We argue that the originate-to-distribute model of lending resulted in the origination of inferior quality of loans in recent years. Using a measure of banks' participation in the OTD market prior to the onset of subprime mortgage crisis, we show that banks with higher OTD participation have higher mortgage default rates in the later periods. These chargeoffs are concentrated in banks that are unable to sell their OTD loans after the disruption in the mortgage market.

Our evidence confirms the popular belief that lack of screening incentive created by the separation of origination from the ultimate bearer of the default risk has been a contributing factor to the current mortgage crisis. More important, our study shows that these incentive problems are severe for poorly capitalized banks and banks that rely less on demand deposits. Thus, large capital base and higher fraction of demand deposits act as disciplining devices for the banks.

These findings have important implications for financial markets and bank regulators. Our results imply that the probability of default of a mortgage depends on the originator of the loan in a predictable way. This can serve as an important input to the pricing models of mortgage-backed securities. Our findings also provide useful inputs to the regulation of financial markets and the determination of capital ratio for the banking sector.

Appendix:Data Details

We obtain our data from the call reports filed by all FDIC-insured commercial banks every quarter. This report includes detailed information on bank's income statement, balance sheet and several off-balance sheet items. In our study, we take the individual bank as our unit of analysis. An alternative will be to use the data at the bank holding company's level. However, holding company level data might be contaminated by the presence of non-banking subsidiaries of banks. In the table below, we describe the construction of key variables used in our study.

- Liquid Assets: We define liquid assets as the sum of cash plus fed funds sold plus government securities (US treasuries and government agency debt) held by the banks. Note that we do not include all securities held by banks, since it also includes mortgage backed securities. In our sample period, these securities are unlikely to serve as a liquidity buffer for the banks. Liquidity ratio is the ratio of liquid assets to total assets.
- Mortgage loans: We take loans granted for 1-4 family residential properties.
- Mortgage chargeoffs: We take chargeoff on the residential 1-4 family mortgages. We use the net measure of mortgage chargeoff, which is computed as chargeoffs minus recovery.
- Originate-to-Distribute Mortgages: We compute the dollar volume of 1-4 family residential mortgages originated by banks with a purpose to sell them off to third parties. This data item is filled by all banks with assets of more than $1 billion as of June 30, 2005 or any bank with less than $1 billion in total assets where there is more than $10 million activity in 1-4 family residential mortgage market for two consecutive quarters. The first quarter in which banks reported this data item is 2006Q3. The data is divided into two broad categories: retail origination and wholesale origination.

  We divide the sum of retail and wholesale origination by the beginning of the quarter 1-4 family mortgage loans to get the measure of OTD in our analysis.
- Loans sold during the quarter: Banks also report the extent of 1-4 family residential mortgage loans sold to third parties during the quarter.

  We scale them by the beginning of the quarter mortgage loans for 1-4 family residential properties to get out first measure of the intensity of loan sale. In the second measure, we add the origination of loans during the same quarter to the beginning of the quarter mortgage loans in the denominator.
- Foreclosure: Starting with 2008Q1, banks have begun to report the extent of 1-4 family residential mortgages serviced for others that are in the process of foreclosures.
- Mortgage securitized and serviced for others: Item RCFDB805 reports the outstanding principal balance of 1-4 family residential mortgages serviced for others with no-recourse or servicer-provided credit enhancements. We scale the foreclosure amount of the previous item by this amount to obtain a measure of the extent of foreclosed mortgages as a fraction of mortgages sold and securitized for others.
- Maturity Gap: We construct 1-year maturity GAP as follows: (loans and leases due to mature and re-price within a year+Securities due to mature or re-price within a year+Fed

Fund Sold+Customers Liability to the Bank for Outstanding Acceptance) minus (Term Deposits due to mature or re-price within a year+Fed Funds Borrowed+Other Liabilities for Borrowed Funds+Banks Liabilities on Customers Outstanding Acceptance). We take the absolute value of this number and scale it by the total assets of the bank to compute the 1-year maturity gap ratio.

References

1. Allen, Franklin, and Douglas Gale, 1994, Financial innovations and risk sharing, MIT Press, Cambridge, MA.
2. Allen, Franklin, and Elena Carletti, 2006, Credit risk transfer and contagion, Journal of Monetary Economics 53, 89-111.
3. Ashcraft, Adam, and Joao Santos, 2007, Has the CDS market lowered the cost of corporate debt?, Working paper, Federal Reserve Bank of New York.
4. Boyd, John, and Ed Prescott, 1986, Financial intermediary coalitions, Journal of Economic Theory 38, 211-232.
5. Brunnermeier, Markus, 2008, Deciphering the 2007-08 Liquidity and Credit Crunch, forthcoming Journal of Economic Perspective.
6. Calomoris C., and C. Kahn, 1991, The Role of Demandable Debt in Structuring Optimal Banking Arrangements, The American Economic Review 81, 497-513.
7. Cebenoyan, A. S., and P. Strahan, 2004, Risk Management, Capital Structure, and Lending at Banks. Journal of Banking & Finance 28, 1943.
8. Dell'Ariccia, Giovanni, Igan, Deniz and Laeven, Luc A., 2008, Credit booms and lending standards: Evidence from the subprime mortgage market, Working Paper.
9. Demyanyk, Yuliya and Van Hemert, Otto, 2008, Understanding the subprime mortgage crisis, Working paper New York University.
10. Doms, Mark, Furlong, Fred and Krainer, John, 2007, Subprime mortgage delinquency rates, FRB San Francisco Working Paper 2007-33.
11. Diamond, Douglas and Philip Dybvig, 1983, Bank Runs, Deposit Insurance, and Liquidity, Journal of Political Economy 91, 401-419.
12. Diamond, Douglas, 1984, Financial intermediation and delegated monitoring, Review of Economic Studies 51, 393-414.
13. Diamond, Douglag, and Raghuram Rajan, 2001, Liquidity risk, liquidity creation, and financial fragility: A theory of banking, Journal of Political Economy, 109, 287-327.
14. Drucker, Steven and Manju Puri, 2005, Banks and Capital Markets: A Survey, Handbook of Empirical Corporate Finance, Edited by B. Espen Eckbo (Elsevier/North-Holland).
15. Drucker, Steven and Manju Puri, 2008, On loan sales, loan contracting, and lending relationships, Forthcoming in Review of Financial Studies.
16. Flannery, Mark, 1994, Debt maturity structure and the deadweight cost of leverage: Optimally financing banking firms, American Economic Review 84, 320-31.
17. Froot, K.A., Scharfstein, D.S., and Stein, J.C., 1993. Risk management: coordinating corporate investments and financing policies. Journal of Finance 5, 16291658.

18. Froot, K.A., and Stein, J.C., 1998, Risk management, capital budgeting, and capital structure policy for financial institutions: An integrated approach 47, 55-82.

19. Gande, A., and A. Saunders, 2007, Are Banks Still Special when There Is a Secondary Market for Loans? Working Paper, New York University.

20. Gordon, Brian, and Adrian D'Silva, 2008, Hedges in the warehouse: The banks get trimmed, Chicago Fed Letter #249.

21. Gorton, G., and G. Pennacchi, 1995, Banks and loan sales: Marketing nonmarketable assets, Journal of Monetary Economics 35, 389411.

22. Gorton, Gary and Andrew Winton, 2002, Financial Intermediation, in Handbook of the Economics of Finance, edited by George Constantinides, Milt Harris and Rene Stulz (Amsterdam: North Holland).

23. Greenlaw David, Jan Hatzius, Anil K Kashyap, and Hyun Song Shin, 2008, Leveraged losses: Lessons from the mortgage market meltdown, US Monetary Policy Forum Conference Draft.

24. Jensen M., and W. Meckling, 1976, Theory of the firm: managerial behavior, agency costs and ownership structure, Journal of Financial Economics 3, 305-360.

25. Holmstrom, Bengt and Jean Tirole 1998, Private and Public Supply of Liquidity, Journal of Political Economy 106, 1-40.

26. Holmstrom, Bengt and Jean Tirole, 1997, Financial Intermediation, Loanable Funds, and the Real Sector, Quarterly Journal of Economics 112, 663-691.

27. Kashyap, Anil K, Raghuram G. Rajan and Jeremy C. Stein, 2002, Banks as Liquidity Providers: An Explanation for the Co-existence of Lending and Deposit-Taking, Journal of Finance 57, 33-74.

28. Keys, Benjamin, Tanmoy Mukherjee, Amit Seru and Vikrant Vig, 2010, Did Securitization Lead to Lax Screening? Evidence From Subprime Loans, Forthcoming, Quarterly Journal of Economics, 125, 2010.

29. Leland, Hayne, and David Pyle, 1977, Information asymmetries, financial structure, and financial intermediation, Journal of Finance 32, 371-387.

30. Loutskina, Elena, 2006, Does securitization affect bank lending: Evidence from bank responses to funding shocks, Working Paper, University of Virginia.

31. Loutskina, Elena and Strahan, Philip, 2007, Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage acceptance rates, Working Paper, University of Virginia.

32. Loutskina, Elena and Strahan, Philip E., 2008, Informed and Uninformed Investment in Housing: The Downside of Diversification, SSRN Working Paper.

33. Mayer, Christopher, and Karen Pence, 2008, Subprime Mortgages: What, Where, and to Whom?, NBER Working Paper.

34. Mian, Atif, and Amir Sufi, 2008, The Consequences of Mortgage Credit Expansion: Evidence from the 2007 Mortgage Default Crisis, Working paper, University of Chicago.

35. Mishkin, Frederic S., 2008, On "Leveraged Losses: Lessons from the Mortgage Meltdown", February 29, 2008.

36. Parlour Christine and Guillaume Plantin, 2008, Loan sales and Relationship Banking, Journal of Finance 63, 1291-1314.

37. Pennacchi, G. 1988. Loan sales and the cost of bank capital, Journal of Finance 43, 37596.

38. Purnanandam, Amiyatosh, 2007, Interest Rate Derivatives at Commercial Banks: An Empirical Investigation, Journal of Monetary Economics 54, 1769-1808.

39. Rajan, Raghuram, 2008, A View of the Liquidity Crisis, mimeo, University of Chicago.

40. Rajan, Uday, Amit Seru and Vikrant Vig, 2009, The Failure of Models that Predict Failure: Distance, Incentives and Defaults, Working Paper.

41. Smith, C.W., Stulz, R., 1985, The determinants of firms' hedging policies, Journal of Financial and Quantitative Analysis, 28, 391-405.

42. Stein, Jeremy, 1998, An Adverse-Selection Model of Bank Asset and Liability Management with Implications for the Transmission of Monetary Policy, RAND Journal of Economics 29, 466-486.

43. Stulz, R., 1984. Optimal hedging policies. Journal of Financial and Quantitative Analysis 19, 127-140.

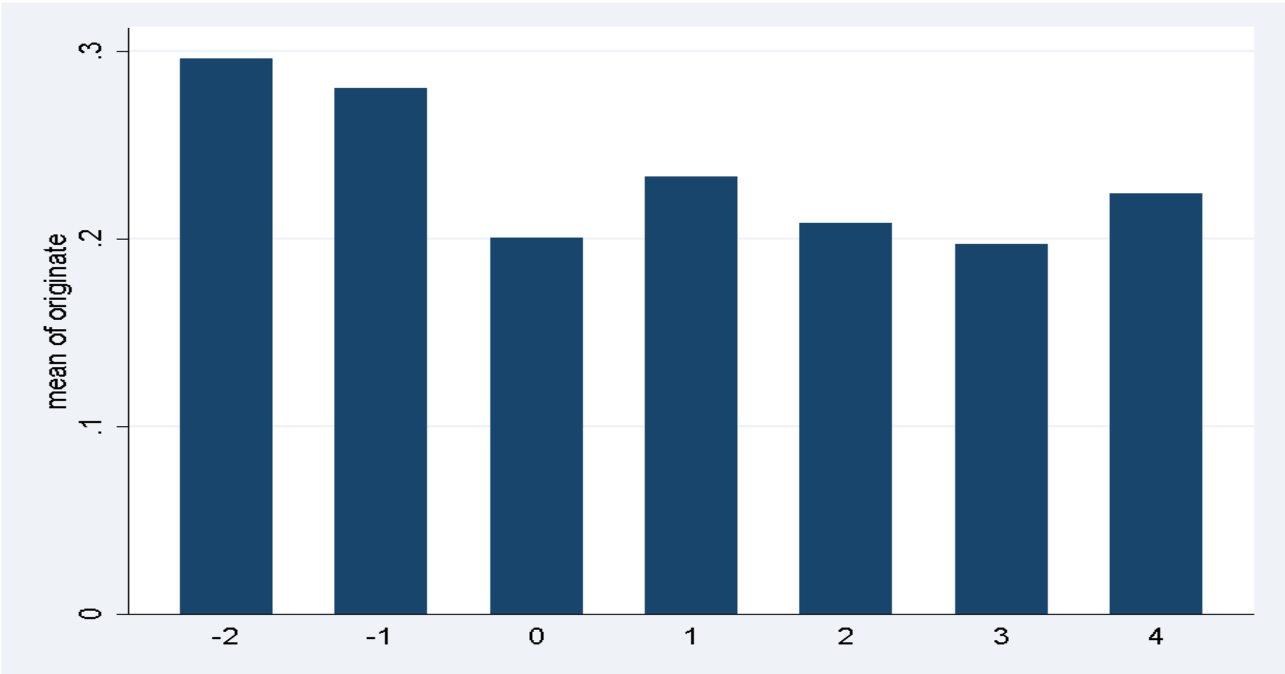
44. Thakor, Anjan, 1996, Capital requirement, monetary policy, and aggregate bank lending: Theory and empirical evidence, Journal of Finance 51, 279-324.

45. Titman, S., and S. Tsyplakov, 2007, Originator Performance, CMBS Structures and Yield Spreads of Commercial Mortgages, University of Texas Working Paper.

46. Tufano, Peter, 2003, Financial innovations, in Handbook of the Economics of Finance, edited by George Constantinides, Milt Harris and Rene Stulz (Amsterdam: North Holland).

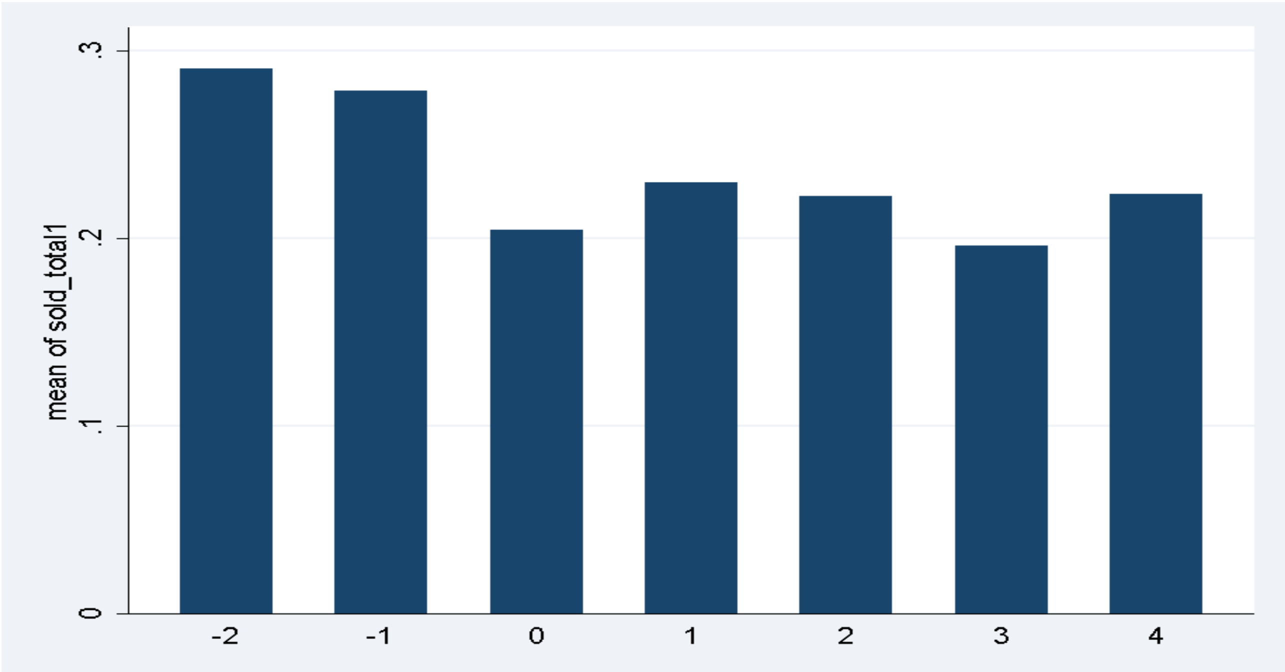
The following figure plots the average origination of loans with a purpose to sell (OTD) in the market as a fraction of mortgage outstanding on a quarterly basis. Quarter zero corresponds to quarter ending on March 31, 2007.

Figure 1: **Mortgage originated to distribute over time**



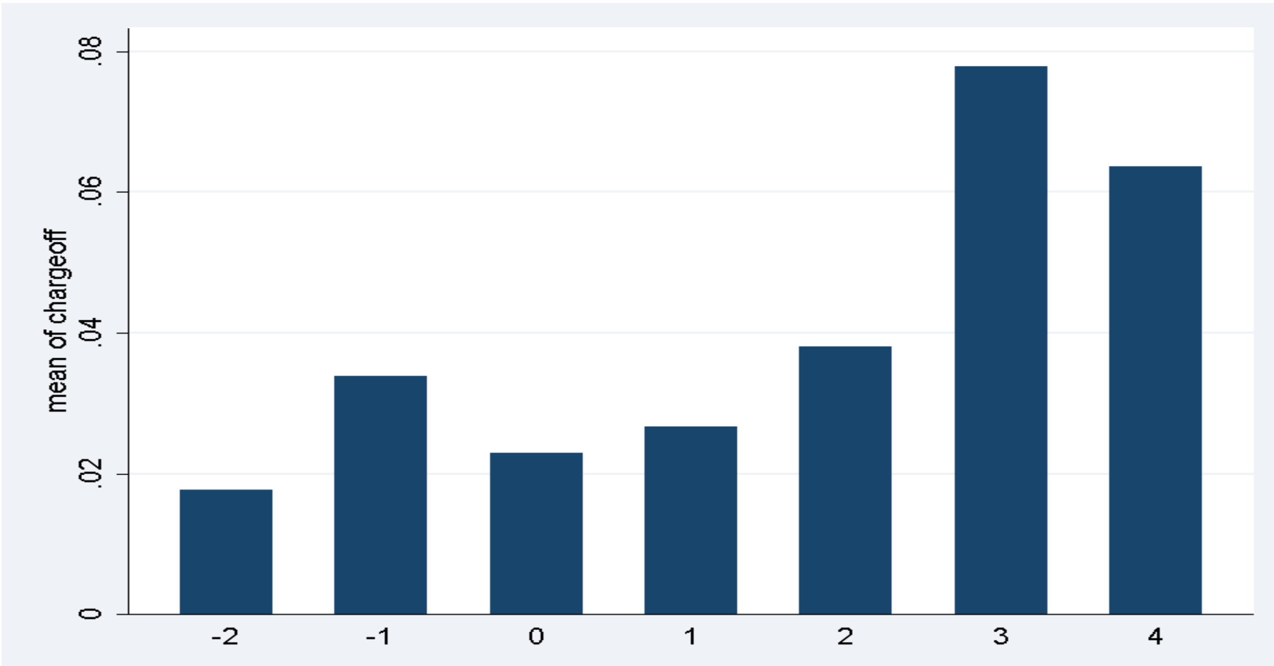
The following figure plots the average of loans sold by banks as a fraction of mortgage outstanding as of the beginning of the quarter. Quarter zero corresponds to quarter ending on March 31, 2007.

Figure 2: **Mortgage sold over time: Model 1**



The following figure plots the average net charge-off as a % of mortgage outstanding on a quarterly basis. Quarter zero corresponds to quarter ending on March 31, 2007.

Figure 3: **Mortgage chargeoff over time**



The following figure plots the average net charge-off (as a % of mortgage outstanding) on bank's mortgage portfolio across two groups of banks sorted on the basis of their participation in the OTD market prior to March 31, 2007, on quarterly basis.

Figure 4: **Mortgage chargeoff and OTD participation**

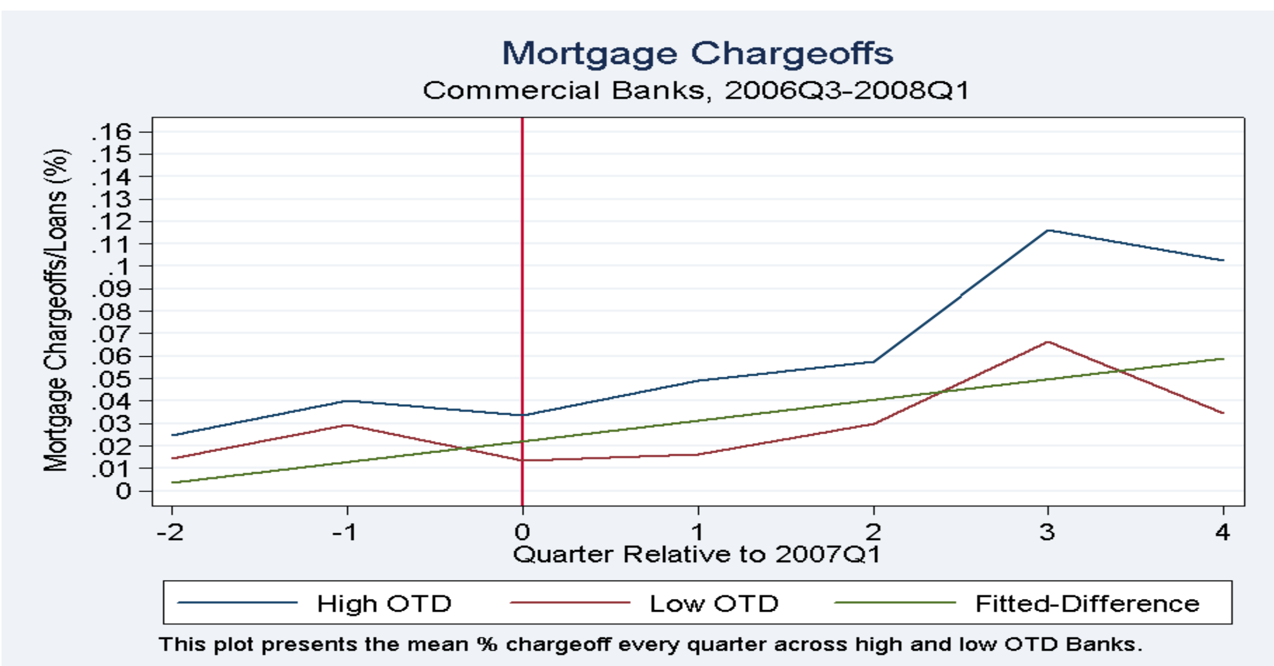
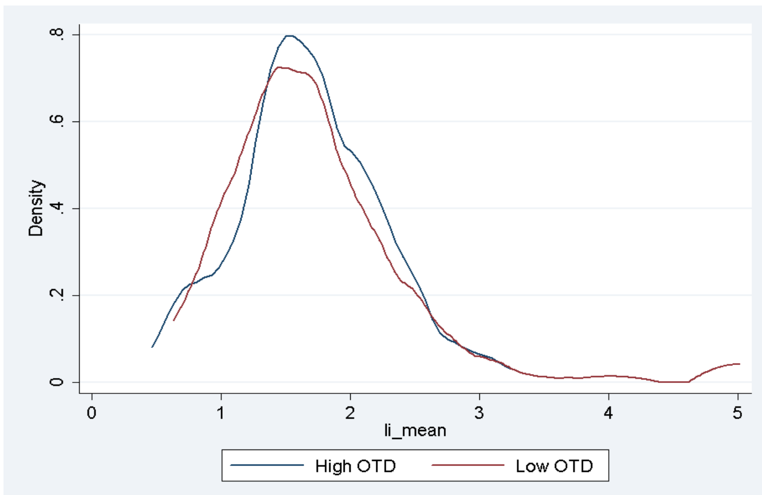


Figure 5: Distribution of Key Characteristics of High and Low OTD Banks After Matching

The plots give the kernel density functions of the key characteristics of the high and low OTD banks after matching. More details on the matching are provided in the paper. The first plot is for the loan-to-income ratios (li_mean); the second plot is for the HUD (Housing and Urban Development) median family income of the MSA in which the property is located.



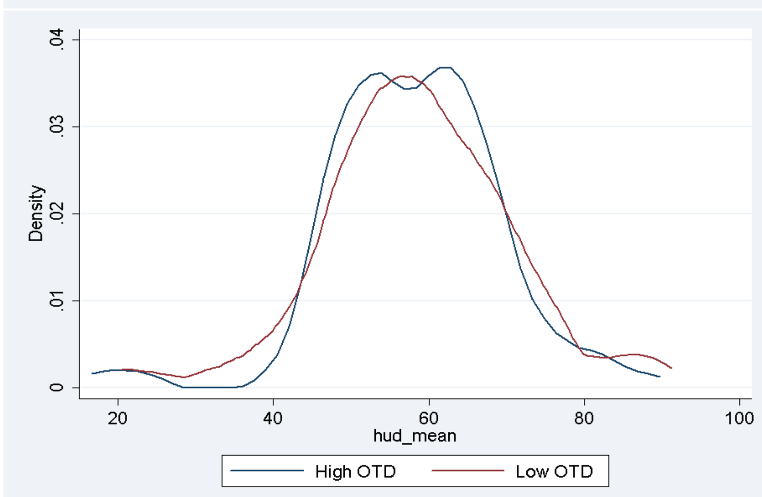


Table 1: **Summary Statistics**

This table provides the summary statistics of key variables used in the study. All variables are computed using call report data for seven quarters starting from 2006Q3 and ending in 2008Q1. We provide the number of observations (n), mean, median, minimum and maximum values for each variable. *ta* is total assets in billions of dollar; *mortgage/ta* is the ratio of mortgages outstanding to total assets, *cil/ta* is the ratio of commercial and industrial loans to total assets; *td/dd* is the ratio of total deposits to total assets; *dd/ta* is the ratio of demand deposits to total deposits; *nii/ta* is the ratio of net interest income to total assets; *chargeoff* measures the chargeoff on mortgage portfolio (net of recoveries) as a percentage of mortgage assets; *npa/ta* is the ratio of non-performing assets to total assets; *mortnpa* is the ratio of non-performing mortgages to total mortgages; *tier1cap* measures the ratio of tier one capital ratio to risk-adjusted assets; *liquid* is the bank's liquid assets to total asset ratio, *absgap* is the absolute value of one-year maturity gap as a fraction of total assets.

variable	**N**	**mean**	**p50**	**min**	**max**
ta	6636.00	4.80	0.80	0.04	133.22
mortgage/ta	6636.00	0.17	0.15	0.00	0.52
cil/ta	6636.00	0.11	0.10	0.00	0.38
td/ta	6636.00	0.78	0.80	0.23	0.92
dd/td	6636.00	0.10	0.08	0.00	0.34
leverage	6636.00	0.90	0.91	0.77	0.94
nii/ta	6636.00	0.90	0.89	0.28	1.68
chargeoff	6636.00	0.04	0.00	-0.08	0.79
npa/ta	6636.00	0.73	0.43	0.00	5.29
mortnpa	6636.00	2.08	1.35	0.00	14.30
tier1cap	6636.00	0.12	0.11	0.07	0.37
liquid	6636.00	0.16	0.13	0.02	0.53
absgap	6636.00	0.15	0.12	0.00	0.56

Table 2: **Intensity of Mortgages Sold**

This table provides the regression results of the following model:

$$sold_{it} = \beta_0 + \beta_1 after_t + \beta_2 preotd_i + \beta_3 after_t * preotd_i + \sum_{k=1}^{k=K} \beta X + \epsilon_{it}$$

The dependent variable, $sold_{it}$, measures bank i's mortgage sale as a fraction of its total mortgage loans at the beginning of quarter t. $after_t$ is a dummy variable that is set to zero for quarters before and including 2007Q1, and one after that. $preotd_i$ is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1. X stands for a set of control variables. Model 1 is estimated using OLS method. Standard errors are clustered at bank level. Models 2 and 3 are estimated with bank fixed-effects. Model 3 excludes banks with more than $10 billion in assets. These models omit *preotd* and *premortgage* as right-hand-side variables since they remain constant across all seven quarters for a given bank. *premortgage* is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4, and 2007Q1. *logta* measures the log of total assets; *cil/ta* is the ratio of commercial and industrial loans to total assets; *liquid* is the bank's liquid assets to total asset ratio, *absgap* is the absolute value of one-year maturity gap as a fraction of total assets. Adjusted R-squared and number of observations are provided in the bottom rows.

	Model 1		Model 2		Model 3	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
preotd	0.9915	(48.46)				
premortgage	-0.0074	(-0.17)				
after	0.0283	(2.31)	0.0213	(2.31)	0.0262	(2.56)
$after * preotd$	-0.2030	(-3.78)	-0.2126	(-6.56)	-0.2154	(-6.63)
$after * premortgage$	0.0117	(0.18)	0.0119	(0.24)	0.0153	(0.29)
logta	-0.0017	(-0.37)	0.0938	(2.76)	0.1084	(2.39)
cil/ta	-0.0466	(-0.50)	-0.5038	(-2.16)	-0.5917	(-2.46)
liquid	0.0281	(0.46)	-0.0654	(-0.72)	-0.0057	(-0.06)
absgap	-0.0159	(-0.31)	0.2537	(3.22)	0.2866	(3.35)
R^2	0.740		0.8784		0.9067	
N	5175		5175		4751	
State dummies	Yes		No		No	
Bank fixed-effect	No		Yes		Yes	
Exclude Large Banks	No		No		Yes	

Table 3: **Mortgage Performance**

This table provides the regression results of the following model:

$$performance_{it} = \mu_i + \beta_1 after_t + \beta_2 after_t * preotd_i + \sum_{k=1}^{k=K} \beta X + \epsilon_{it}$$

The dependent variable, $performance_{it}$, is measured by either the mortgage chargeoffs or the non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. $after_t$ is a dummy variable that is set to zero for quarters before and including 2007Q1, and one after that. $preotd_i$ is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1. μ_i denotes bank fixed effects; X stands for a set of control variables. *premortgage* is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4, and 2007Q1. *logta* measures the log of total assets; *cil/ta* is the ratio of commercial and industrial loans to total assets; *liquid* is the bank's liquid assets to total asset ratio; *absgap* is the absolute value of one-year maturity gap as a fraction of total assets. Adjusted R-squared and number of observations are provided in the bottom rows.

	All Banks				Excludes Large Banks			
Dependent Var:	Model 1 Chargeoffs		Model 2 NPA		Model 3 Chargeoffs		Model 4 NPA	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$after$	0.0106	(2.20)	0.3536	(4.34)	0.0113	(2.28)	0.3649	(4.15)
$after * preotd$	0.0414	(4.86)	0.3419	(2.70)	0.0414	(4.77)	0.3261	(2.56)
$after * premortgage$	0.0046	(0.23)	0.6931	(1.88)	-0.0060	(-0.29)	0.3337	(0.87)
$logta$	0.0733	(3.85)	0.1850	(0.86)	0.0660	(3.45)	0.5087	(1.97)
cil/ta	0.1870	(2.10)	3.4651	(2.16)	0.1611	(1.77)	3.2800	(1.89)
$liquid$	0.0703	(1.57)	1.7068	(2.18)	0.0703	(1.42)	0.7267	(0.92)
$absgap$	-0.0654	(-2.12)	-2.7004	(-4.96)	-0.0674	(-2.05)	-2.6319	(-4.56)
R^2	0.3023		0.6683		0.2825		0.6556	
N	6636		6636		6167		6167	

Table 4: **Mortgage Performance and Inability to Sell**

This table provides the fixed effect regression results for the following model:

$$performance_{it} = \mu_i + \beta_1 after_t + \beta_2 after_t * stuck_i + \sum_{k=1}^{k=K} \beta X + \epsilon_{it}$$

The dependent variable, $performance_{it}$, is measured by either the mortgage chargeoffs (Models 1,2 and 3) or the non-performing mortgages (Models 4,5 and 6) of bank i during quarter t. $after_t$ is a dummy variable that is set to zero for quarters before and including 2007Q1, and one after that. $stuck_i$ is the difference between loans originated before 2007Q1 and loans sold after this quarter. μ_i denotes bank fixed effects; X stands for a set of control variables. $preotd_i$ is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1; *premortgage* is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4, and 2007Q1. *logta* measures the log of total assets; *cil/ta* is the ratio of commercial and industrial loans to total assets; *liquid* is the bank's liquid assets to total asset ratio; *absgap* is the absolute value of one-year maturity gap as a fraction of total assets. Adjusted R-squared and number of observations are provided in the bottom rows.

	Chargeoffs						Non-Performing Assets					
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$after$	0.0116	(2.44)	0.0112	(2.33)	0.0120	(2.41)	0.3516	(4.41)	0.3629	(4.43)	0.3784	(4.28)
$after * stuck$	0.0882	(5.04)	0.0787	(2.55)	0.0748	(2.88)	0.8368	(2.87)	1.1255	(2.02)	1.5141	(3.30)
$after * premortgage$	0.0017	(0.08)	0.0021	(0.10)	-0.0080	(-0.39)	0.6693	(1.82)	0.6567	(1.78)	0.2942	(0.76)
logta	0.0804	(4.25)	0.0797	(4.15)	0.0723	(3.75)	0.2552	(1.20)	0.2765	(1.30)	0.6347	(2.47)
cil/ta	0.1951	(2.21)	0.1930	(2.17)	0.1696	(1.87)	3.4836	(2.15)	3.5500	(2.20)	3.4509	(1.96)
liquid	0.0645	(1.44)	0.0650	(1.46)	0.0686	(1.39)	1.6475	(2.14)	1.6312	(2.12)	0.6934	(0.88)
absgap	-0.0606	(-1.97)	-0.0610	(-1.99)	-0.0640	(-1.96)	-2.6511	(-4.90)	-2.6375	(-4.90)	-2.5631	(-4.47)
$after * preotd$			0.0056	(0.39)	0.0074	(0.58)			-0.1704	(-0.74)	-0.3621	(-1.90)
R^2	0.3041		0.3040		0.2840		0.6691		0.6691		0.6569	
N	6636		6636		6167		6636		6636		6167	
Exclude Large Banks	No		No		Yes		No		No		Yes	

Table 5: **The Effect of Bank Capital**

This table provides the regression results of the following fixed effect model:

$$\begin{aligned} performance_{it} &= \mu_i + \beta_1 after_t + \beta_2 after_t * preotd_i + \beta_2 after_t * lowcap_i \\ &+\beta_3 after_t * preotd_i * lowcap_i + \sum_{k=1}^{k=K} \beta X + \epsilon_{it} \end{aligned}$$

The dependent variable, $performance_{it}$, is measured by either the mortgage chargeoffs or the non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. $after_t$ is a dummy variable that is set to zero for quarters before and including 2007Q1, and one after that. $preotd_i$ is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1; $lowcap_i$ equals one for banks that fall in bottom quartile of equity capital, zero otherwise; μ_i denotes bank fixed effects; X stands for a set of control variables. *premortgage* is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4, and 2007Q1. *logta* measures the log of total assets; *cil/ta* is the ratio of commercial and industrial loans to total assets; *liquid* is the bank's liquid assets to total asset ratio; *absgap* is the absolute value of one-year maturity gap as a fraction of total assets. Adjusted R-squared and number of observations are provided in the bottom rows.

	All Banks				Excludes Large Banks			
	Model 1		Model 2		Model 3		Model 4	
Dependent Var:	Chargeoffs		NPA		Chargeoffs		NPA	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$after$	0.0103	(2.07)	0.3536	(4.18)	0.0115	(2.21)	0.3688	(4.01)
$after * preotd$	0.0289	(3.05)	0.1740	(1.24)	0.0281	(2.95)	0.1451	(1.05)
$after * preotd * lowcap$	0.0424	(2.14)	0.5714	(1.94)	0.0466	(2.28)	0.6308	(2.09)
$after * lowcap$	0.0004	(0.07)	-0.0111	(-0.13)	-0.0020	(-0.34)	-0.0315	(-0.35)
$after * premortgage$	0.0050	(0.25)	0.6974	(1.89)	-0.0060	(-0.29)	0.3336	(0.87)
$logta$	0.0723	(3.81)	0.1735	(0.81)	0.0655	(3.45)	0.5026	(1.97)
cil/ta	0.1895	(2.13)	3.4965	(2.18)	0.1628	(1.80)	3.3025	(1.90)
$liquid$	0.0708	(1.58)	1.7133	(2.18)	0.0698	(1.41)	0.7206	(0.91)
$absgap$	-0.0689	(-2.24)	-2.7459	(-5.04)	-0.0704	(-2.15)	-2.6728	(-4.63)
R^2	0.3043		0.6690		0.2849		0.6565	
N	6636		6636		6167		6167	

Table 6: **The Effect of Demand Deposits**

This table provides the regression results of the following fixed effect model:

$$performance_{it} = \mu_i + \beta_1 after_t + \beta_2 after_t * preotd_i + \beta_2 after_t * lowdep_i + \beta_3 after_t * preotd_i * lowdep_i + \sum_{k=1}^{k=K} \beta X + \epsilon_{it}$$

The dependent variable, $performance_{it}$, is measured by either the mortgage chargeoffs or the non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. $after_t$ is a dummy variable that is set to zero for quarters before and including 2007Q1, and one after that. $preotd_i$ is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1; $lowdep_i$ equals one for banks that do not fall in the top quartile of demand deposit to total liability ratio, zero otherwise; μ_i denotes bank fixed effects; X stands for a set of control variables. *premortgage* is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4, and 2007Q1. *logta* measures the log of total assets; *cil/ta* is the ratio of commercial and industrial loans to total assets; *liquid* is the bank's liquid assets to total asset ratio; *absgap* is the absolute value of one-year maturity gap as a fraction of total assets. Adjusted R-squared and number of observations are provided in the bottom rows.

	All Banks				Excludes Large Banks			
	Model 1		Model 2		Model 3		Model 4	
Dependent Var:	Chargeoffs		NPA		Chargeoffs		NPA	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$after$	0.0056	(0.93)	0.3147	(2.82)	0.0076	(1.25)	0.3375	(2.91)
$after * preotd$	0.0165	(1.22)	-0.2301	(-1.16)	0.0168	(1.25)	-0.2354	(-1.19)
$after * preotd * lowdep$	0.0388	(2.26)	0.8815	(3.49)	0.0386	(2.23)	0.8757	(3.46)
$after * lowdep$	0.0062	(1.19)	0.0475	(0.53)	0.0047	(0.88)	0.0338	(0.37)
$after * premortgage$	0.0034	(0.17)	0.6465	(1.74)	-0.0070	(-0.34)	0.2974	(0.77)
$logta$	0.0740	(3.90)	0.2049	(0.96)	0.0667	(3.50)	0.5258	(2.05)
cil/ta	0.2030	(2.27)	3.7985	(2.37)	0.1790	(1.96)	3.6519	(2.10)
$liquid$	0.0699	(1.57)	1.7134	(2.21)	0.0726	(1.47)	0.7875	(1.00)
$absgap$	-0.0653	(-2.13)	-2.6907	(-4.95)	-0.0668	(-2.04)	-2.6158	(-4.53)
R^2	0.3047		0.6706		0.2849		0.6580	
N	6636		6636		6167		6167	

Table 7: **Matched Sample Analysis I**

This table reports the estimation results of fixed-effect regressions on matched sample of high and low OTD banks. Banks are matched on geographical location of their mortgage portfolios, the borrowers' loan-to-income ratio, the borrowers' annual income and the bank's size. In Model 1 the dependent variable is the non-performing mortgage loans of the banks. In Models 2-5, the dependent variable is the quarterly mortgage chargeoffs. The definition of variables and details of the model estimation are provided in the paper. Adjusted R-squared and number of observations are provided in the bottom rows.

	Model 1		Model 2		Model 3		Model 4		Model 5	
Dep Var:	NPA		Chargeoff							
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$after$	0.6356	(4.37)	0.0046	(0.47)	0.0082	(0.84)	0.0078	(0.73)	0.0060	(0.50)
$after * preotd$	0.8725	(3.28)	0.0784	(4.73)	-0.0360	(-1.42)	0.0259	(2.15)	0.0434	(2.39)
$after * premortgage$	-0.1994	(-0.34)	0.0476	(1.15)	0.0438	(1.06)	0.0522	(1.26)	0.0529	(1.28)
$logta$	-0.2618	(-0.48)	0.0898	(2.50)	0.1089	(2.97)	0.0877	(2.46)	0.0891	(2.45)
cil/ta	-1.9274	(-0.74)	-0.0308	(-0.19)	-0.0507	(-0.33)	-0.0707	(-0.45)	-0.0287	(-0.18)
$liquid$	3.7072	(1.66)	0.0889	(0.78)	0.0541	(0.47)	0.1100	(0.98)	0.0819	(0.72)
$absgap$	-5.6962	(-4.61)	-0.0534	(-0.73)	-0.0454	(-0.63)	-0.0735	(-1.02)	-0.0556	(-0.76)
$after * stuck$					0.1814	(3.95)				
$after * lowcap$							-0.0058	(-0.61)		
$after * preotd * lowcap$							0.1093	(3.83)		
$after * lowdep$									-0.0030	(-0.32)
$after * preotd * lowdep$									0.0474	(1.72)
R^2	0.6573		0.3081		0.3131		0.3146		0.3030	
N	1925		1925		1925		1925		1925	

Table 8: **Matched Sample Analysis II**

This table reports the estimation results of fixed-effect regressions on matched sample of high and low OTD banks. Banks are matched on geographical location of their mortgage portfolios, bank size, the borrowers' loan-to-income ratio and the rate spread on these loans. In Model 1 the dependent variable is the non-performing mortgage loans of the banks. In Models 2-5, the dependent variable is the quarterly mortgage chargeoffs. The definition of variables and details of the model estimation are provided in the paper. Adjusted R-squared and number of observations are provided in the bottom rows.

	Model 1		Model 2		Model 3		Model 4		Model 5	
Dep Var:	NPA		Chargeoff							
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$after$	0.2996	(2.07)	0.0099	(1.09)	0.0117	(1.28)	0.0138	(1.44)	0.0069	(0.68)
$after * preotd$	0.8557	(3.30)	0.0663	(4.13)	0.0075	(0.23)	0.0294	(1.88)	0.0357	(1.11)
$after * premortgage$	0.6496	(1.08)	0.0257	(0.67)	0.0204	(0.53)	0.0183	(0.48)	0.0306	(0.80)
$logta$	-0.1408	(-0.29)	0.0718	(2.23)	0.0826	(2.45)	0.0700	(2.19)	0.0708	(2.21)
cil/ta	0.4446	(0.19)	0.1497	(0.88)	0.1360	(0.81)	0.1242	(0.75)	0.1567	(0.93)
$liquid$	3.0403	(1.60)	0.2100	(1.72)	0.1870	(1.53)	0.2052	(1.70)	0.2067	(1.70)
$absgap$	-5.1597	(-4.57)	-0.0204	(-0.32)	-0.0143	(-0.23)	-0.0273	(-0.44)	-0.0197	(-0.31)
$after * stuck$					0.1122	(2.01)				
$after * lowcap$							-0.0094	(-1.10)		
$after * preotd * lowcap$							0.1218	(3.90)		
$after * lowdep$									0.0034	(0.38)
$after * preotd * lowdep$									0.0432	(1.18)
R^2	0.6394		0.2767		0.2790		0.2927		0.2785	
N	2212		2212		2212		2212		2212	

Table 9: **Matched Sample Analysis III**

This table reports the estimation results of fixed-effect regressions on matched sample of high and low OTD banks. We match small banks with large OTD lending with large banks with little-to-no OTD lending. In Model 1 the dependent variable is the non-performing mortgage loans of the banks. In Models 2-5, the dependent variable is the quarterly mortgage chargeoffs. The definition of variables and details of the model estimation are provided in the paper. Adjusted R-squared and number of observations are provided in the bottom rows.

	Model 1		Model 2		Model 3		Model 4		Model 5	
Dep Var:	NPA		Chargeoff							
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$after$	0.2588	(1.55)	0.0106	(0.79)	0.0097	(0.72)	0.0101	(0.72)	0.0202	(1.34)
$after * preotd$	0.7155	(3.01)	0.0243	(2.68)	-0.0397	(-1.99)	0.0138	(1.77)	0.0031	(0.27)
$after * premortgage$	-0.7004	(-1.09)	-0.0170	(-0.38)	-0.0167	(-0.37)	-0.0113	(-0.25)	-0.0028	(-0.06)
$logta$	2.5199	(3.57)	0.1707	(2.72)	0.2004	(3.11)	0.1645	(2.57)	0.1707	(2.71)
cil/ta	3.6488	(0.65)	0.9380	(2.92)	0.7679	(2.50)	0.8518	(2.68)	0.9542	(2.95)
$liquid$	1.8198	(0.57)	0.3261	(1.60)	0.2875	(1.46)	0.2976	(1.47)	0.3253	(1.60)
$absgap$	-5.5830	(-3.42)	-0.4338	(-3.73)	-0.4011	(-3.57)	-0.4025	(-3.47)	-0.4335	(-3.74)
$after * stuck$					0.1337	(3.11)				
$after * lowcap$							-0.0137	(-1.09)		
$after * preotd * lowcap$							0.1301	(2.80)		
$after * lowdep$									-0.0155	(-1.20)
$after * preotd * lowdep$									0.0273	(1.67)
R^2	0.6699		0.2896		0.3082		0.3095		0.2898	
N	959		959		959		959		959	

Table 10: **Shrinkage in Loan Spread**

This table provides the dispersion in loan spread across high (above median) and low (below median) OTD banks. Panel A is for all banks, Panel B for the matched sample. We provide three measures of dispersion in log loan spreads: standard deviation, the difference between the 75^{th} and the 25^{th} percentiles, and the difference between the 90^{th} and the 10^{th} percentiles. Shrinkage measures the difference in dispersion across the high and low OTD banks. Bartlett p-value is for the null hypothesis that the variance of loan spreads for the high OTD group equals the variance of loan spreads for the low OTD group.

	Panel A: All Banks			Panel B: Matched Sample		
	High OTD	Low OTD	Shrinkage	High OTD	Low OTD	Shrinkage
Standard Deviation	0.2140	0.2639	0.0499	0.2007	0.2645	0.0638
P75-P25	0.2952	0.3613	0.0661	0.2608	0.3753	0.1146
P90-P10	0.5956	0.6855	0.0899	0.4980	0.6959	0.1979
Bartlett's p-value			0.0001			0.0001

Table 11: **OTD and Foreclosures**

This table provides the cross-sectional Tobit regression results for the extent of foreclosures on mortgages serviced for others. We provide the marginal effects of the right-hand-side variables evaluated at their mean values. The dependent variable, $foreclosure_i$, measures the amount of mortgage under foreclosure serviced by bank i for others scaled by the bank's average mortgage loans during 2006Q3, 2006Q4 and 2007Q1. This model is estimated with 935 cross-sectional observation from the second quarter of 2008. $preotd_i$ is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1. $logta$ is the log of total assets; $mortgage/ta$ is the ratio of mortgage loans to total assets; *tier1cap* is the tier one capital ratio of bank; *floatmort* is the ratio of mortgages due to reprice within a year scaled by total mortgages; *liquid* is the bank's liquid assets to total asset ratio. All explanatory variables are measured by computing their averages during quarters 2006Q3, 2006Q4 and 2007Q1.

	Model 1		Model 2	
	Estimate	t-val	Estimate	t-val
$preotd$	0.0649	(3.25)	0.0736	(3.61)
$logta$	0.0504	(7.87)	0.0484	(7.27)
$mortgage/ta$	0.2017	(2.07)	0.1837	(1.83)
$tier1cap$			-0.0845	(-0.30)
$floatmort$			-0.1336	(-1.81)
$liquid$			0.1231	(1.02)
$PseudoR^2$	0.1875		0.1928	
N	935		935	