Originate-to-distribute Model and the Subprime Mortgage Crisis

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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 mortgage lending 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. Overall, we provide evidence that lack of screening incentives coupled with leverage-induced risk-taking behavior significantly contributed to the current subprime mortgage crisis. (*JEL* G11, G12, G13, G14)

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 2009). 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.

As a part of their core operation, banks 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 this expertise due to market incompleteness, regulatory reasons, or some other frictions. For example, regulatory capital requirements and frictions

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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 regulatory capital, and achieve better liquidity risk management.[2]

These benefits of the OTD model come at a cost. As the lending practice shifts from an originate-to-hold to an originate-to-distribute model, it begins to interfere with the originating banks' screening and monitoring incentives (Pennacchi 1988; Gorton and Pennacchi 1995; Petersen and Rajan 1994; Parlour and Plantin 2008). It is this cost of the OTD model that lies at the root of our analysis. Banks make lending decisions based on a number of borrower characteristics. While some of these characteristics are easy to credibly communicate to third parties, there are soft pieces of information that cannot be easily verified by parties other than the originating institution itself. Thus, as the originating institution sheds the credit risk, and as the distance between the originator and the ultimate holder of risk increases, loan officers' ex ante incentives to collect soft information decrease (see Stein 2002 and Rajan, Seru, and Vig 2009). If the ultimate holders of credit risk do not completely appreciate the true credit risk of mortgage loans, then it is easy to see the resulting dilution in the originator's screening incentives. However, it is not a necessary condition for the dilution in screening standards to occur. For example, if the cost of communicating soft information is so high that all originators are pooled together by the outside investors, then the originator's ex ante screening incentive goes down even without pricing mistakes by the ultimate investors. The screening incentives can deteriorate further if credit-rating agencies make mistakes, as some observers have argued, in assessing the true credit risk of mortgage-backed securities.

Our key hypothesis is that banks with aggressive involvement in the OTD market had lower screening incentives, which in turn resulted in the origination of loans with excessively poor soft information by these banks. The OTD model of lending 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

1 Allen and Carletti (2006) analyze 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 (2005) for a survey of different theories behind loan sales.

3 The mortgage market was functioning normally until 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, Hatzius, Kashyap, and Shin 2008).

pressure in the middle of 2007, banks with a higher volume of OTD loans were stuck with large quantities of 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 90 days of loans (Mishkin 2008). If banks with a high volume of 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 mortgage quality.

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 a large quantity of origination in the immediate pre-disruption period were unable to sell their OTD loans in the post-disruption period. We then show that banks with higher participation with the OTD model in the pre-disruption period had significantly higher mortgage chargeoffs and defaults by their borrowers in the immediate post-disruption period. 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., for banks that were left with large quantities of undesired mortgage portfolios.

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. In order to provide convincing support for the diluted screening incentives hypothesis, it is important to rule out the effect of observable differences in the quality of loans issued by high- and low-OTD banks on mortgage default rate. We conduct several tests using detailed loan-level data from the Home Mortgage Disclosure Act (HMDA) to address this issue. In these tests, we compare the default rate of high- and low-OTD banks that are matched along several dimensions of borrowers' observable default risk, properties' location, and the bank's characteristics. We show that our results remain strong in the matched subsamples. Thus, the effect of OTD lending on mortgage default rates is not an artifact of observable differences in the borrowers' credit risk, the geographical location of high- and low-OTD banks, or differences in the originating bank's other characteristics, such as size and cost of capital.

We continue our investigation by analyzing the interest rates charged by high- and low-OTD banks during the pre-disruption period. If a bank screens its borrowers carefully on unobservable dimensions, then it is more likely to charge different interest rates to observationally similar borrowers (see Rajan, Seru, and Vig 2009). Therefore, we 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. Consistent with the lax screening hypothesis, we find evidence of tighter distribution for the high-OTD banks in our sample.

In our final test, we focus on the determinants of poor screening by the high-OTD banks. We find that the effect of pre-disruption OTD lending on 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 a lower capital base should do no worse than the well-capitalized banks. In contrast, theoretical models such as Thakor (1996) and Holmstrom and Tirole (1997) suggest that banks with lower capital have a lower screening incentive due to the risk-shifting problem. Our results support the presence of lax screening incentives behind the origination of such loans. We also find that the effect of OTD loans on mortgage default is concentrated among banks with a lower dependence on demand deposits.[4] The result supports the view that demand deposits worked as a governance device for commercial banks, as argued by Calomoris and Kahn (1991), Flannery (1994), and Diamond and Rajan (2001). Our study shows that banks that were primarily funded by non-demandable or market-based wholesale debt were the main originators of poor-quality OTD loans.

There is a growing literature in this area, with important contributions from Keys et al. 2010; Mian and Sufi 2010; Loutskina and Strahan 2008; Doms, Furlong, and Krainer 2007; Mayer and Pence 2008; Dell'Ariccia, Igan, and Laeven 2008; Demyanyk and Van Hemert 2009; and Titman and Tsyplakov 2010. We make three unique contributions to the literature. This is one of the first academic studies that compares default rates of banks that originated loans to sell to third parties with banks that originated loans for their own portfolios. Our findings complement those of Keys et al. (2010), who analyze default rates of *securitized* loans above and below the FICO score of 620. In addition to the advantage of comparing sold versus retained loans, our analysis also shows that the dilution in screening standards was not confined to a particular range of borrowers' FICO scores. Instead, it was a far more widespread phenomenon that occurred throughout the banking sector. Second, we focus on lending decisions of institutions that are directly originating loans from borrowers or through their brokers. Thus, our study analyzes the screening behavior of economic agents that are directly responsible for originating loans at the front end of the lending-securitization channel. Third, our study advances the literature by showing that a bank's capital position and reliance on non-demandable debt have significant effects on its screening incentives.

Overall, our findings have important implications for banking regulations. In addition, we contribute to the credit-risk pricing literature by showing that in an information-sensitive asset market, the issuer's capital position and liability

[4] Since the capital structure and the 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.

structure have important implications for the pricing of assets in the secondary market. It is important to note that our results come from a period of turmoil in the financial markets. To draw strong policy implications, one obviously has to compare these costs of securitization 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 2009).[5] It is also worth pointing out that the role of other macroeconomic factors, such as the aggregate borrowing and savings rate and monetary policies across the globe, cannot be ignored as a potential explanation for the crisis (see Allen 2009). Our study is essentially cross-sectional in nature, which limits our ability to comment on the role of these macroeconomic factors.

The rest of the article is organized as follows. Section 1 describes the data and provides descriptive statistics. Section 2 presents empirical results relating OTD market participation to mortgage defaults. Section 3 provides the matched sample results. Section 4 explores the linkages with capital position and liability structure, and Section 5 concludes.

1. Data

We use two sources of data for our study: the call report database for bank information and the HMDA (Home Mortgage Disclosure Act) database for loan details. All Federal Deposit Insurance Corporation (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 banking business. As the mortgage sale and securitization activities grew in recent years, there have been concomitant improvements in the quality of reporting with respect to these items as well.

Beginning with the third quarter of 2006, banks started to report two key items regarding their mortgage activities: (a) the origination of 1–4 family residential mortgages during 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 by smaller banks if they exceed \$10 million in their mortgage-selling activities. The data, in effect, are available for all banks that participate significantly in the OTD market.

[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 the secondary loan sales market on the bank-specialness.

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 mortgage loans from the beginning of the quarter.

We obtain two measures of mortgage quality from the call reports: (1) chargeoffs on 1–4 family residential mortgages; and (2) non-performing assets (NPAs) for this category; i.e., mortgage loans that are past due or delinquent. We use net chargeoffs (net of recoveries) as the first proxy of loan quality. It measures the immediate effect of mortgage defaults on a bank's profitability. However, chargeoffs may be subject to the reporting bank's discretionary accounting rules. Mortgage NPAs, on the other hand, are free from this bias and provide a more direct measure of the borrowers' default rate.

We get information on the banks' assets, profitability, mortgage loans, liquidity ratio, capital ratios, and several other variables from the call report. It is important to construct these variables in a consistent manner across quarters 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, to 2008Q1. The reporting requirement has been fairly stable over this time period, and we check every quarter's format to ensure that our data are 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. The HMDA was enacted by Congress in 1975 to improve reporting requirements in the mortgage lending business. The HMDA database 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 a certain threshold. We match the call report and HMDA database for 2006 to obtain information on the quality of borrowers and geographical location of loans made by banks during the pre-disruption period.

1.1 Descriptive statistics

Our sample consists of all banks with available data on mortgage origination for resale from 2006Q3 to 2008Q1. We intersect this sample with banks covered in the HMDA database in 2006. 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 charts. In Figure 1, we plot the quarterly average of loans originated for resale as a

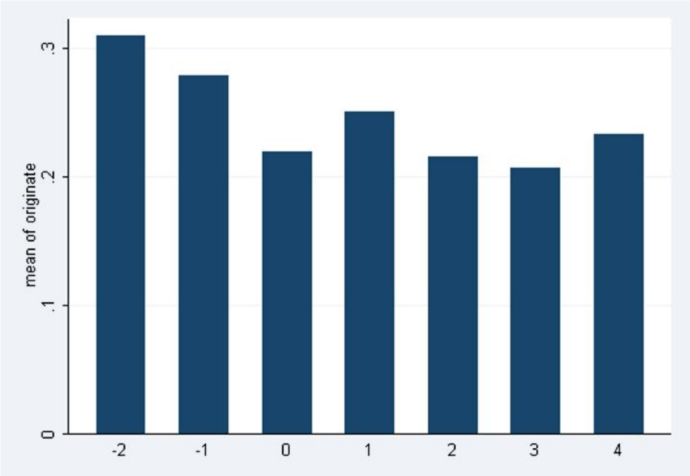

Figure 1
Mortgage originated for distribution over time
The figure plots the ratio of OTD loans to total mortgages on a quarterly basis. We plot the average value of this ratio across all banks with available information in the sample. Quarter zero corresponds to the quarter ending on March 31, 2007.

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 in or before 2007Q1. Overall, these graphs show 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 on a quarterly basis. As expected, the quarterly chargeoffs have increased steadily since 2007Q1. The chargeoffs increased fourfold from 2007Q1 to 2007Q4—a very significant increase for highly leveraged financial institutions. We find a similar trend for non-performing mortgages as well (unreported).

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 $5.9 billion (median $1.1 billion). These numbers show that our sample represents relatively large

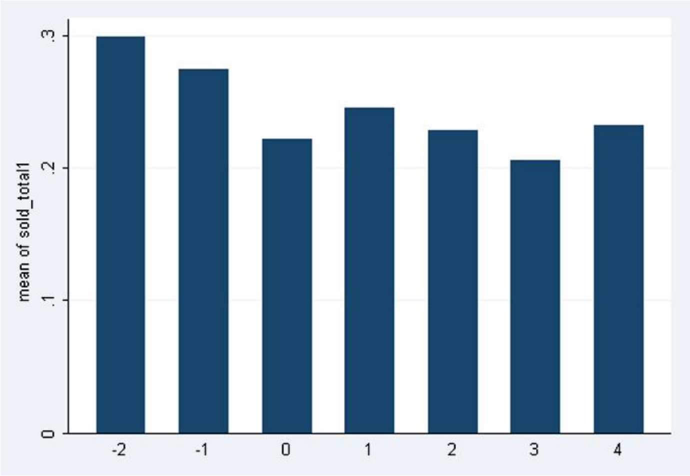

Figure 2
Mortgage sold over time
The figure plots the extent of loans sold as a fraction of mortgages outstanding as of the beginning of the quarter. We plot the average value of this ratio across all banks with available information in the sample. Quarter zero corresponds to the quarter ending on March 31, 2007.

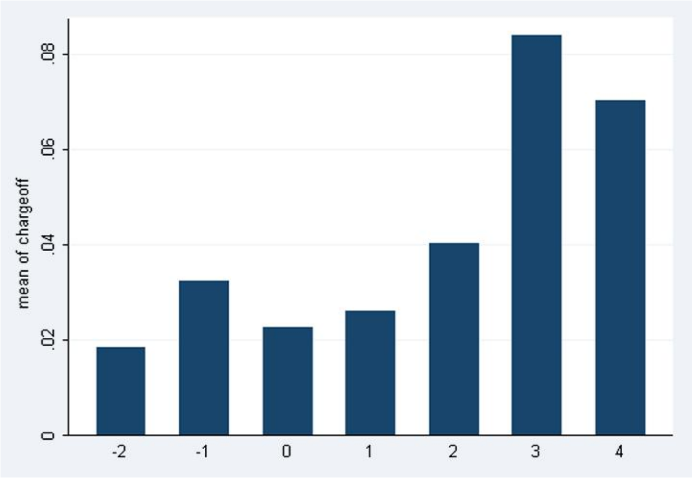

Figure 3
Mortgage chargeoff over time
The figure plots the average net chargeoff as a percentage of mortgage outstanding on a quarterly basis. Quarter zero corresponds to the quarter ending on March 31, 2007.

banks, due to the fact that we require data on OTD mortgage origination and sale for a bank 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.

Table 1
Summary statistics

variable	N	mean	p50	min	max
ta	5397.00	5.92	1.05	0.06	168.65
mortgage/ta	5397.00	0.17	0.15	0.01	0.49
cil/ta	5397.00	0.11	0.10	0.00	0.39
td/ta	5397.00	0.78	0.80	0.44	0.92
dd/td	5397.00	0.09	0.08	0.01	0.33
leverage	6636.00	0.90	0.91	0.77	0.94
nii/ta	5397.00	0.89	0.87	0.32	1.51
chargeoff(%)	5397.00	0.04	0.00	−0.07	0.79
npa/ta(%)	5397.00	0.73	0.44	0.00	5.40
mortnpa(%)	5397.00	2.03	1.35	0.00	13.86
tier1cap	5397.00	0.11	0.10	0.07	0.29
liquid	5397.00	0.15	0.12	0.02	0.50
absgap	5397.00	0.14	0.11	0.00	0.51
preotd	771.00	0.23	0.05	0.00	3.06

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 dollars; *mortgage/ta* is the ratio of 1–4 family residential mortgages outstanding to total assets; *cil/ta* is the ratio of commercial and industrial loans to total assets; *td/ta* is the ratio of total deposits to total assets; *dd/td* 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 to risk-adjusted assets; *liquid* is the bank's liquid assets to total assets ratio, *absgap* is the absolute value of one-year maturity gap as a fraction of total assets. *preotd* measures the originate-to-distribute loans, i.e., mortgages originated with a purpose to sell, as a fraction of total mortgages. This variable is constructed at the bank level based on its average quarterly values during 2006Q3, 2006Q4, and 2007Q1.

Figure 4 provides a graphical preview of our results. 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 the 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 one-third of the *preotd* distribution. We track 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, this figure shows that both groups have experienced a significant increase in chargeoffs over time. However, there is a remarkable difference in their slopes. While both groups started at similar levels of chargeoffs in 2006Q3 and they show parallel trends before the beginning of the crisis, the high-OTD group's chargeoffs increased five times by the end of the sample period as compared with a significantly lower increase of about two to three times for the low-OTD group. 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

[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*.

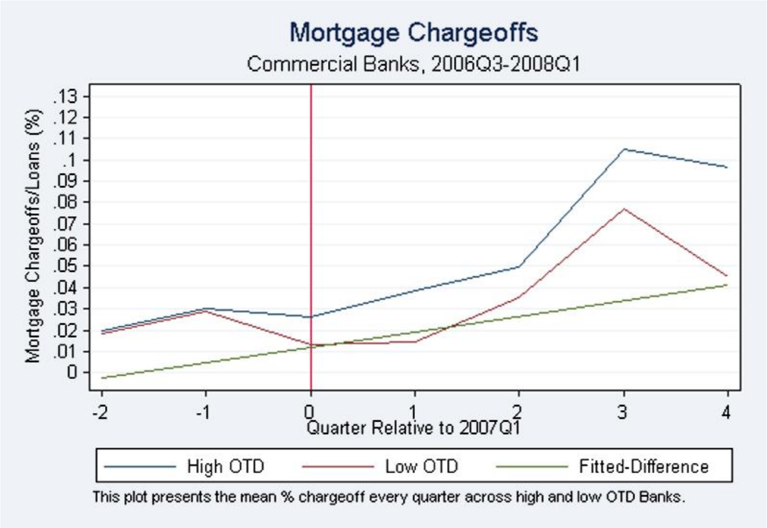

Figure 4
Mortgage chargeoff and OTD participation
The figure plots the average net chargeoff (as a percentage of mortgage outstanding) on the bank's mortgage portfolio across two groups of banks sorted on the basis of their participation in the OTD market prior to March 31, 2007.

remarkable linear increase over this time period. The difference in default rate becomes especially high after a couple of quarters from the onset of the crisis.

In summary, we find that banks with higher OTD participation before the subprime mortgage crisis increased 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 article.

2. Mortgage Default Rate 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 relationship between a bank's mortgage default rate and the extent of its participation in the OTD market.

2.1 Empirical design and identification strategy

Our key argument is that banks with aggressive involvement in the OTD model of lending did not actively screen their borrowers along the soft information dimension. The OTD model allowed them to benefit from the origination fees without bearing the ultimate credit risk of the borrowers. These banks originated large amounts of loans with inferior soft information, which were subsequently sold to investors. As long as the secondary loan market had enough liquidity, banks were able to offload their originated loans without any disruption. The delay from origination to the final sale of these loans did not impose significant credit risk on the originating banks during normal periods. However, 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 was exacerbated by the early pay default warranties that the sellers of OTD loans typically provide to their buyers for the first 90 days after the loan sale (Mishkin 2008). Therefore, immediately after the liquidity shock of summer 2007, these banks were left with disproportionately large amounts of OTD mortgage loans that they had originated with an intention to sell but could not sell. If these loans had relatively lower screening standards, then we expect to find relatively higher mortgage default rates for high-OTD banks in quarters immediately following the onset of the crisis as compared with otherwise similar low-OTD banks that originated most of their loans with an intention to keep them on their balance sheets.

To test this hypothesis in an idealized experimental setting, we need two randomly selected groups of banks that are identical in every respect except for their involvement in the OTD method of lending. To be more precise, we want to compare banks with varying intensity of OTD lending that have made loans to borrowers with observationally similar risk characteristics. This will allow us to estimate the effect of OTD lending on the screening efforts of banks along the soft information dimension without contaminating the results from differences in observable risk characteristics of the borrowers. Because we have only observational data, we control for these differences by including several bank and borrower characteristics in the regression model. More importantly, we conduct our tests in a difference-in-difference setting with carefully chosen matched samples of high- and low-OTD banks. In these tests, we attempt to find pairs of banks that are similar and have made loans to observationally similar borrowers before the crisis. Then we exploit differences along the OTD dimension in these samples to estimate the effect of OTD lending on screening efforts.

2.1.1 Extent of mortgage resale. Since our identification strategy relies on banks' inability to sell their loans in the secondary markets, we first document evidence in support of this argument. 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

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

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 a positive and significant coefficient on this variable because 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 before and after 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 importantly, we also include a variable $premortgage$ that measures the extent of mortgages made by the 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. 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 the OLS method. All standard errors are clustered at the bank level to account for correlated errors across all quarters for the same bank (see Bertrand, Duflo, and Mullainathan 2004). 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 a large and positive coefficient on the $preotd$ variable. The coefficient on the interaction of $after$ and $preotd$ is negative and highly significant. In this specification, we find a positive coefficient on the $after$ dummy variable. In unreported tests, we estimate an OLS regression of $sold_{it}$ on $after$ and obtain a coefficient of $-0.031(t - stat = -1.97)$ on $after$. Therefore, the sharp decline in the loan resale is concentrated within the set of high $preotd$ banks.

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 the mortgage market on the high-OTD banks. $preotd$ and $premortgage$ are omitted from this model because they are captured in the bank fixed effects. Our identification comes from the interaction of $after$ with $preotd$. In Model 2, we find a significant negative coefficient on the interaction term, which confirms that banks with large OTD loans in the pre-disruption period suffered a 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 a significant negative coefficient on $after$ (coefficient

8 Our results are similar without the inclusion of the $premortgage$ variable in the regression models.

Table 2
Intensity of mortgages sold

	Model 1		Model 2		Model 3	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
preotd	0.9591	(54.64)				
premortgage	0.0403	(0.85)				
after	0.0273	(1.95)	0.0182	(1.23)	0.0205	(1.24)
*after*preotd*	−0.1889	(−3.34)	−0.2037	(−3.74)	−0.2120	(−3.86)
*after*premortgage*	0.0163	(0.21)	0.0235	(0.29)	0.0428	(0.49)
logta	−0.0031	(−0.54)	0.1475	(2.88)	0.1575	(2.44)
cil/ta	−0.0248	(−0.22)	−0.8606	(−2.74)	−0.7744	(−2.40)
liquid	0.0339	(0.48)	−0.0292	(−0.21)	0.0570	(0.38)
absgap	−0.0320	(−0.55)	0.2866	(2.79)	0.3171	(2.82)
R^2	0.8156		0.9039		0.9054	
N	4476		4476		4100	
State dummies	Yes		No		No	
Bank fixed effect	No		Yes		Yes	
Exclude large banks	No		No		Yes	

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 the OLS method. 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. All standard errors are clustered at the bank level.

estimate of −0.0251 with t-statistics of −2.74). 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 because it is often argued that large money-centric banks have a different business model than regional and local banks. We find that our results are equally strong after excluding these large banks from the sample.

These results are economically significant as well. For example, a one-standard-deviation increase in OTD lending prior to the disruption results in a decline of 10% in selling intensity after the crisis based on the estimates of Model 2. Overall, these results are 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 undesired loans; i.e., loans that were initially intended to be sold but could not be sold due to an unexpected decline in the market conditions.

2.2 Mortgage defaults

We now estimate the effect of OTD lending on a bank's quarterly mortgage default rates with the following bank fixed-effect regression model:

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

The dependent variable of this model measures the default rate of the mortgage portfolio of bank i in quarter t. We use two measures of default: net-chargeoffs and non-performing mortgages; i.e., mortgages that are in default for more than 30 days. We scale them by the bank's total mortgage loans measured as of the beginning of the quarter. μ_i stands for bank fixed effects, and X_{it} is a vector of bank characteristics.[9] The coefficient on the $after$ variable captures the time trend in default rate before and after the mortgage crisis. The coefficient on the interaction term (i.e., $after_t * preotd_i$) measures the change in chargeoffs/NPAs around the crisis period across banks with varying intensities of participation in the OTD market prior to the crisis. Said differently, β_2 measures the change in default rate for banks that originated loans primarily to sell them to third parties, as compared with the corresponding change for banks that originated loans primarily to retain them on their own balance sheets. We include the interaction of $after$ with $premortgage$ to ensure that the relationship between OTD loans and mortgage performance is not simply an artifact of higher involvement in mortgage lending by higher OTD banks.[10]

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 the 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.

Table 3 provides the results. 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

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9 In an alternative specification, we also estimate this model without bank fixed effects (similar to the one described in the previous section for the extent of mortgage resale). The advantage of this model is that it also allows us to estimate the coefficient on $preotd$. However, we prefer the bank fixed-effect approach as it allows us to control for unobservable factors that are time-invariant and unique to a bank. All key results remain similar for the alternative econometric model.

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

Table 3
Mortgage defaults

	All Banks				Excludes Large Banks			
	Model 1 Chargeoffs		Model 2 NPA		Model 3 Chargeoffs		Model 4 NPA	
Dependent Var:	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
after	0.0116	(1.91)	0.3411	(3.03)	0.0134	(2.03)	0.3076	(2.52)
*after*preotd*	0.0420	(2.76)	0.4439	(2.44)	0.0428	(2.76)	0.4015	(2.21)
*after*premortgage*	0.0060	(0.21)	0.6600	(1.22)	−0.0062	(−0.20)	0.4261	(0.82)
logta	0.0925	(4.15)	0.2266	(0.51)	0.0776	(2.67)	0.6896	(1.42)
cil/ta	0.2010	(1.65)	2.6103	(1.37)	0.1662	(1.32)	2.2626	(1.13)
liquid	0.0745	(1.24)	1.3732	(0.90)	0.1089	(1.64)	−0.1540	(−0.14)
absgap	−0.0672	(−1.59)	−3.2639	(−3.85)	−0.0742	(−1.64)	−3.1248	(−3.66)
R^2	0.3805		0.7297		0.3621		0.7135	
N	5397		5397		4977		4977	

This table provides the regression results of the following fixed-effects model:

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

The dependent variable, $default_{it}$, 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 assets 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 standard errors are clustered at the bank level.

on a bank's mortgage default rates during the post-disruption quarters. In the chargeoff regression model (Model 1), we find a positive and significant coefficient of 0.0420 on $after * preotd$. In Model 2, we repeat the analysis with non-performing mortgages as the measure of loan quality and again find a positive and significant coefficient on the interaction term. These effects are economically large as well. For example, based on the estimates of Model 2, a one-standard-deviation increase in $preotd$ results in an increase of about 11% in the mortgage default rate as compared with the unconditional sample mean. We repeat our analysis after excluding large banks from the sample and obtain similar results.[11]

In our next test, we model 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 first 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

[11] In an unreported robustness exercise, we drop the first two quarters after the beginning of the crisis from our sample. We do so to allow more time for the mortgages to default after the beginning of the crisis. Our results become slightly stronger for this specification.

Table 4
Mortgage default and inability to sell

	All Banks				Excludes Large Banks			
	Model 1 Chargeoffs		Model 2 NPA		Model 3 Chargeoffs		Model 4 NPA	
Dependent Var:	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
after	0.0131	(2.18)	0.3113	(2.81)	0.0148	(2.25)	0.2791	(2.35)
*after*stuck*	0.0922	(3.03)	1.4342	(3.64)	0.0940	(3.02)	1.2756	(3.39)
*after*premortgage*	0.0000	(0.00)	0.5888	(1.11)	−0.0110	(−0.35)	0.3892	(0.75)
logta	0.1004	(4.64)	0.3684	(0.85)	0.0855	(3.02)	0.8078	(1.67)
cil/ta	0.1964	(1.62)	2.3276	(1.25)	0.1675	(1.34)	2.0930	(1.07)
liquid	0.0633	(1.05)	1.1788	(0.83)	0.1047	(1.60)	−0.2045	(−0.19)
absgap	−0.0603	(−1.43)	−3.1394	(−3.79)	−0.0690	(−1.54)	−3.0421	(−3.59)
R^2	0.3818		0.7330		0.3635		0.7162	
N	5397		5397		4977		4977	

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

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

The dependent variable, $default_{it}$, is measured by either the mortgage chargeoffs or the non-performing mortgages 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. $stuck_i$ measures 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. *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 assets 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 standard errors are clustered at the bank level.

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. 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.[12]

We re-estimate the $default$ regression model by replacing $preotd$ with $stuck$. Results are presented in Table 4. We find a large positive coefficient on the interaction term $preotd * stuck$ in Model 1. In unreported tests, we run a horse race between $after * preotd$ and $after * stuck$ and find that the effect of OTD loans on mortgage chargeoffs mainly comes from the variation in the $stuck$ variable. Similar results hold for mortgage default rate using NPA as the dependent variable (see Model 2). Models 3 and 4 show that our results are robust to the exclusion of large banks. 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.

12 It is worth pointing out that this measure is not a perfect proxy for $stuck$ loans because it does not directly match loan origination with selling at the loan-by-loan level. However, in the absence of detailed loan-level data, it is a reasonable proxy for the cross-sectional dispersion of $stuck$ loans at the bank level.

Overall, we show that OTD loans were of inferior quality because banks that were stuck with these loans in the post-disruption period had disproportionately higher chargeoffs and borrower defaults. While these results are consistent with the hypothesis of dilution in screening standards of high-OTD banks, there are two important alternative explanations: (a) Do high-OTD banks experience higher default rates because of observable differences in their borrowers' characteristics? and (b) Do these banks make riskier loans because they have a lower cost of capital (e.g., see Pennacchi 1988)? Our key challenge is to establish a causal link from OTD lending to mortgage default rate that is not explained away by these differences. Since the pullback in liquidity happened at the same time for all banks, we need to be especially careful in ruling out the effect of macroeconomic factors from the screening effect of $preotd$ on mortgage defaults. We extend our study in two directions to address these concerns. We first use a series of matched sample tests using detailed loan-level data to compare banks that made loans to observationally equivalent borrowers before the onset of the crisis. The key idea behind these tests is to compare borrowers that look similar on the hard information dimension so that we can attribute higher default rates of high-OTD banks to their lower underwriting standards in a clear manner. In our second set of tests, we exploit the variation in mortgage default rates within the set of high-OTD banks. In particular, we analyze the effect of banks' liability structure on the quality of OTD loans to isolate the effect of screening standards. These tests also help us understand the key driving forces behind the origination of poor-quality OTD loans.

3. Matched sample analysis

We use the Home Mortgage Disclosure Act (HMDA) database to obtain information on the characteristics of mortgages made by commercial banks during 2006. HMDA was enacted by Congress in 1975 to improve disclosure and promote fairness in the mortgage lending market. The HMDA database 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, and loan amount along with a host of borrower and geographical characteristics on a loan-by-loan basis. We match bank-level call report data with loan-level HMDA data using the FDIC certificate number (call report data item RSSD 9050), FRS identification number (RSSD 9001), and OCC charter number (RSSD 9055) 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.

3.1 Matching based on observable borrower characteristics

Are our results completely driven by differences in observable borrower and loan characteristics of high- and low-OTD banks? We construct a matched sample of high- and low-OTD banks that are similar on key observable dimensions of credit risk 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 a similar geographical area to observationally similar borrowers.

We first match on the geographical location of properties to control for the effect of changes in house prices for loans made by high- and low-OTD banks. We 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 are different. There can be considerable variation in housing returns within a state or even within a metropolitan statistical area (MSA) (e.g., see Goetzmann and Spiegel 1997). Our choice of state-level matching is driven purely by empirical data limitations. As we show later, our matched sample is well balanced along several important characteristics, such as the median household income of the neighborhood, that are shown to explain the within-MSA variation in house prices. In unreported robustness tests, we carry out a matched sample analysis based on matching within the MSA and find similar results. Since our sample size drops considerably as we narrow the geographical unit of matching, all results in the article are based on state-level matching.

We obtain two key measures of the borrower's credit quality from the HMDA dataset: (1) loan-to-income ratio; and (2) borrower's annual income. We compute the average income and the average loan-to-income ratio of all loans made by a bank during 2006 on a bank-by-bank basis. 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: (1) below \$100 million; (2) between \$100 million and \$1 billion; and (3) 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.[13] 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 average income and average loan-to-income ratio of their borrowers.[14] From this subset, we take the bank with the closest average loan-to-income ratio as the matched bank. We match without replacement to find unique matching banks.

Our goal is to find pairs of banks that have made mortgages to observationally equivalent borrowers, but with varying intensity of OTD loans. We

13 We have estimated the model without this restriction, and all results remain similar.

14 Similar results hold if we narrow this band to 25%.

have conducted several alternative matching criteria by changing the cutoffs for bank size, borrower's income, and loan-to-income ratio. Our results are robust. To save space, we provide estimation results for the base model only. Due to the strict matching criteria, our sample size drops for this study. We are able to match 180 high-OTD banks using this methodology.[15]

Given the matching criteria, this sample is dominated by regional banks. The average asset size of banks in this matched sample is $1.71 billion for the high-OTD banks and $1.65 billion for the low-OTD banks. In Figure 5, we plot the distribution of loan-to-income ratio and borrower's annual income across high- and low-OTD banks in the matched sample. Not surprisingly, the two distributions are almost identical. In unreported tests, we find that these two groups are well balanced along several geographical dimensions such as neighborhood median income and the population of the census tract. Thus our banks are matched along the socioeconomic distance as well, which provides further confidence in the comparability of house price changes across these two groups (see Goetzmann and Spiegel 1997). In unreported analysis, we compare several other characteristics across the two groups and analyze them using the 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 bank fixed-effect estimation results in Table 5. Since our results remain similar for both measures of mortgage default, to save space we report results based on non-performing assets only. We find a positive and significant coefficient of 0.89–0.90 on the interaction term $after * preotd$ in Models 1 and 3. Thus, even after conditioning our sample to banks that are comparable along several risk characteristics and property locations, banks that engaged in a higher fraction of OTD lending experienced higher default rates on their mortgage portfolios in quarters just after the onset of the crisis. Models 2 and 4 of the table use $after * stuck$ as the key right-hand-side variable to assess the impact of OTD lending on mortgage default rates for banks that are more likely to be stuck with these loans. We find strong results. Banks that originated a significant amount of mortgage loans with an intention to sell them to third parties, but could not offload them in the secondary market, suffered much higher mortgage default rates.

In economic terms, our estimation shows that banks with one-standard-deviation-higher OTD lending have a mortgage default rate that is about 0.45% higher. This represents a default rate that is 32% higher than the unconditional sample median of this variable. The economic magnitude of the matched sample results are stronger than the base case specification presented in Table 3.

15 Since we impose a restriction of balanced panel in our study, in regressions we lose few observation due to the non-availability of other data items for all seven quarters. Our results remain robust to the inclusion of these observations in the sample.

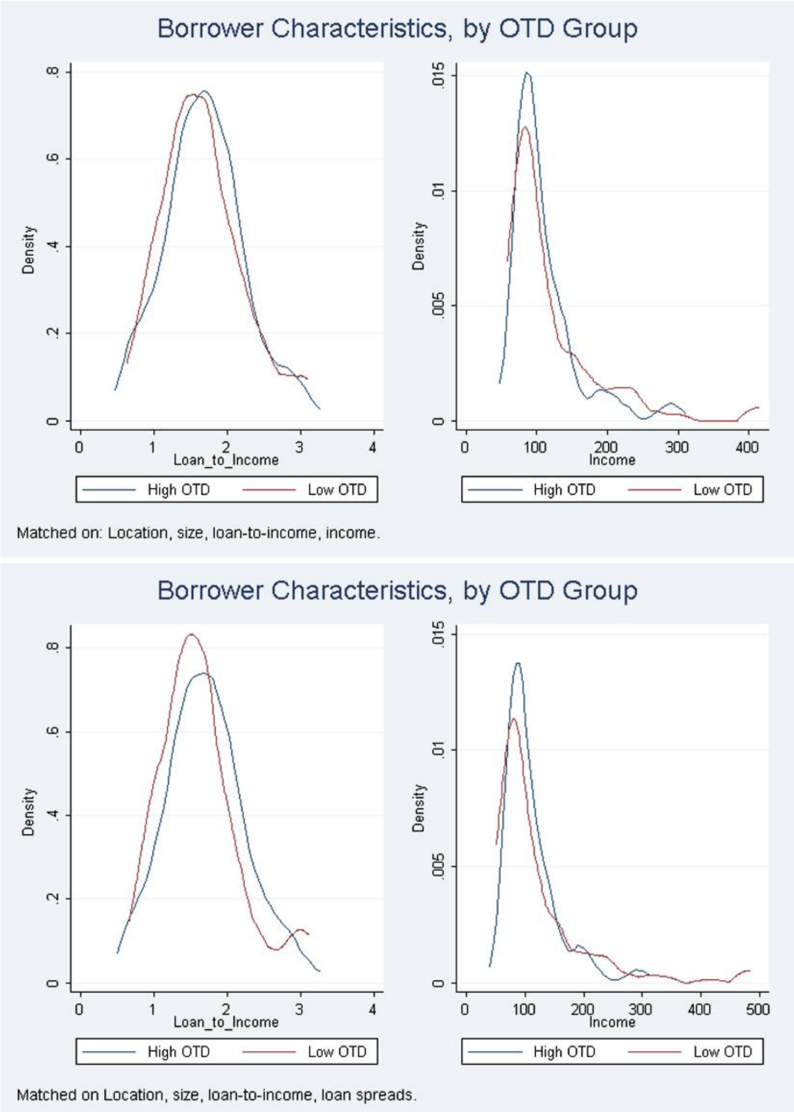

Figure 5
Distribution of key characteristics of high- and low-OTD banks after matching
The plots give the kernel density functions of the key characteristics of the high- and low-OTD banks after matching. More details on the matching are provided in the article. The first plot is for the loan-to-income ratios; the second plot is for the borrowers' annual income.

The coefficient on $after * preotd$ is almost twice as much as the base case that uses all bank-quarter observations. However, we cannot compare these two estimates directly because they are estimated on different samples.

Table 5
Matched sample analysis: Base case

	Model 1 NPA		Model 2 NPA		Model 3 NPA		Model 4 NPA	
Dependent Var:	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
after	0.5657	(6.28)	0.5422	(6.45)	0.4044	(2.15)	0.3649	(1.97)
*after*preotd*	0.8997	(2.83)			0.9043	(2.94)		
*after*stuck*			2.3613	(3.89)			2.3898	(4.19)
*after*premortgage*					0.3076	(0.38)	0.2376	(0.31)
logta					0.6920	(0.72)	0.9455	(1.02)
cil/ta					1.9596	(0.66)	2.0078	(0.69)
absgap					−5.6376	(−3.78)	−5.4404	(−3.74)
liquid					0.5862	(0.18)	−0.0657	(−0.02)
R^2	0.7039		0.7113		0.7136		0.7212	
N	2289		2289		2289		2289	

This table reports the estimation results of fixed-effect regressions on a 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. The dependent variable is the non-performing mortgage loans of banks in a given quarter. The definitions of variables and details of the model estimation are provided in the article. Adjusted *R*-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

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, bank size, or other bank characteristics.

3.2 Matching based on interest rates

Our results suggest that OTD mortgages performed much worse even after conditioning on observable borrower characteristics. This leads to two possibilities: (1) these loans were different on unobservable dimensions and the originating banks properly priced these unobservable factors to account for the higher risk; or (2) the originating banks didn't expend enough resources in screening these borrowers because the loans would be subsequently sold to third parties. Although 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 conduct a specific matched sample analysis to separate these two hypotheses. By definition, it is 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 this fact must 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. The 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 then match banks based on these averages.

For every high-OTD bank, we first find a set of low-OTD banks that meet the following criteria: (1) they primarily operate in the same state as the high-OTD bank; (2) they are in the same size group; (3) they are within 50% of the average loan-to-income ratio of the high-OTD bank; and (4) they are within 50% of the average loan spread of the high-OTD bank. 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 areas at similar rates. We compare the distribution of key borrower characteristics for this matched sample as well. As expected, we find that the high- and low-OTD banks in this sample have borrowers with similar loan-to-income ratio, income, loan security, and neighborhood income. We plot the distribution of loan-to-income ratio and the borrowers' income across these groups in Figure 5. The two distributions fall mostly in the common support zone. In unreported analysis, we compare these characteristics with formal statistical tests. Based on the Kolmogorov-Smirnov test for equality of distribution, we find that these two groups are statistically indistinguishable from each other on each of these dimensions. 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, high- and low-OTD banks in this sample differ in the extent of OTD loans made during the pre-disruption period. Thus, this sample exploits the variation along the OTD dimension, keeping several observable characteristics 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 subsample. If, in contrast, riskier loans were made without properly incorporating the effect of unobservable risk in loan pricing, then we are likely to see differences in the performance of these loans even in this subsample.

This test also allows us to overcome some of the data limitations of the HMDA dataset. Although the HMDA database is one of the most comprehensive loan-level data sources available for mortgage loans, it omits some relevant information about the borrower's credit risk, such as FICO scores. Our matching exercise in the earlier section is based on the assumption that characteristics such as loan-to-income ratio, borrower's income, neighborhood income, and property location capture a significant part of the default risk of loan applicants. The matched sample exercise of this section allows us to control for any omitted variables, such as FICO scores that may be relevant for the banks' credit decision. Information on FICO score or any other variables

Table 6
Matched sample analysis: Average loan spread charged

	Model 1 NPA		Model 2 NPA		Model 3 NPA		Model 4 NPA	
Dependent Var:	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
after	0.5060	(5.58)	0.4911	(5.79)	0.2791	(1.53)	0.2505	(1.40)
*after*preotd*	0.6557	(2.28)			0.6880	(2.44)		
*after*stuck*			1.7369	(3.13)			1.8194	(3.33)
*after*premortgage*					0.4686	(0.64)	0.4364	(0.60)
logta					0.4861	(0.86)	0.6906	(1.22)
cil/ta					0.3309	(0.12)	0.3722	(0.13)
absgap					−4.5193	(−3.31)	−4.5168	(−3.29)
liquid					−2.1793	(−1.35)	−2.3290	(−1.46)
R^2	0.7049		0.7098		0.7118		0.7170	
N	2205		2205		2205		2205	

This table reports the estimation results of fixed-effect regressions on a 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 average rate spread on the subprime loan portfolio of the bank. The dependent variable is the non-performing mortgage loans of the banks in a given quarter. The definition of variables and details of the model estimation are provided in the article. Adjusted *R*-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

used in the process of lending should ultimately be reflected in the rate that banks charge their borrowers. Thus, by exploiting the variation along the OTD dimension, while keeping the interest rates similar, we are able to more precisely estimate the effect of securitization on screening.

Table 6 shows the results. In Models 1 and 2, we estimate the effect of $preotd$ and $stuck$ variables on mortgage default rates without controlling for other bank characteristics. Models 3 and 4 include control variables as well. We find strong evidence that banks that originated a large volume of mortgages that were intended to be sold in the OTD market experienced larger mortgage default on their portfolios in quarters immediately following the crisis. The effect is stronger for banks that were unable to sell these loans. A one-standard-deviation increase in OTD lending in the pre-crisis period results in an increase of 0.38% in the mortgage default rate after the crisis. This increase is approximately 26% of the matched sample's median mortgage default rate.

Even for banks that charged similar rates to their borrowers and made most of their loans in the same geographical area, the performance of high-OTD banks is significantly worse in the post-disruption period. Conditional on interest rates, there should be no relationship between OTD lending and post-crisis default rates if these two groups of loans were made with equal screening efforts. However, if high-OTD loans were granted without proper screening on unobservable dimensions, then we are likely to find higher default rates for high-OTD banks even within this sample. The evidence of this section suggests that OTD loans were made without proper screening on unobservable dimensions.

3.3 Other tests

To complement the results discussed in the previous section, we conduct an additional matched sample test in which we match banks based on the fraction of high-risk loans made during 2006. We compute the fraction of subprime loans made by a bank by computing the ratio of high-spread loans to total loans based on the HMDA dataset. High-spread loans are defined as first-lien loans with a rate spread of more than 3% or second-lien loans with a rate spread of more than 5%. Our matching exercise is the same as in the previous section, except that now we ensure that the fraction of subprime loans (i.e., high-interest-rate loans) made by these banks are similar. In unreported results, we find that OTD lending has a strong effect on mortgage default rate even in this subsample. The estimated economic magnitudes are similar to the interest-rate-based matched sample results of the previous section.

In the preceding analyses, we create carefully matched pairs of high- and low-OTD banks that have similar characteristics. Depending on the matching criteria, we obtain different samples of high- and low-OTD banks, and we show that our key results remain similar across these subsamples. A limitation of this approach is that we conduct our experiments with smaller samples due to the strict matching requirements. Therefore, as a complement to these tests, we use regression methods to control for differences in borrowers' risk characteristics. We estimate the following model:

$$default_{it} = \mu_i + \beta_1 after_t + \beta_2 after_t * preotd_i + \sum_{m=1}^{m=M} \beta_m after_t * risk_{im} + \sum_{k=1}^{k=K} \beta_k X_{ikt} + \epsilon_{it}.$$

$risk_i$ represents a vector of borrowers' default risk for bank i. We interact these measures with $after$ to separate out the effect of borrower risk characteristics on default rates after the crisis from the bank's OTD lending. We use several measures of default risk, such as loan-to-income ratio, annual income, average interest rate charged by the bank, fraction of subprime loans in a bank's portfolio, and the fraction of low-documentation loans in its portfolio. Our results remain robust to this alternative specification. To save space, we do not present these results in the article.

3.4 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 a 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 that of larger banks having little to no involvement in the OTD model of lending. Our assumption is that it is unlikely that a small bank, even after engaging in the OTD model of lending, has a lower cost of capital than a bank that is several times bigger. 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 a higher cost of capital with the performance of non-OTD banks with a relatively lower cost of capital.

We compute the bank's average assets during the pre-disruption quarters (i.e., 2006Q3, 2006Q4, and 2007Q1) and classify them into the small bank group if their assets are 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 the 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 a loan-to-income ratio closest to that of the matched bank. Given the strict nature of matching, our sample drops considerably for this analysis. We are able to obtain a match for 83 small banks by this method. The average asset size of high-OTD banks in this sample is $600 million, whereas the low-OTD banks have an average asset size of about $8.76 billion.

We re-estimate our models for this subsample and present the results in Table 7. Our results remain strong. The high-OTD small banks originated 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.

3.5 Shrinkage in loan spreads

In this section, we provide more direct evidence in support of the dilution in screening standards 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 in which two originating banks are faced with similar pools of borrowers based on observable characteristics. Bank *S* screens the applicants, evaluates their true creditworthiness based on privately observed signals, and grants loans at a fair price. Bank *NS* does not screen its borrowers and offers them a standard rate conditional on observable signals. In this model, the *S*

Table 7
Matched sample analysis: Small to big

	Model 1 NPA		Model 2 NPA		Model 3 NPA		Model 4 NPA	
Dependent Var:	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
after	0.4577	(4.18)	0.4377	(4.36)	−0.0232	(−0.11)	−0.0922	(−0.44)
*after*preotd*	0.8384	(2.33)			0.8665	(2.38)		
*after*stuck*			2.0376	(2.60)			2.2099	(2.81)
*after*premortgage*					1.4795	(1.43)	1.4727	(1.40)
logta					2.3183	(1.77)	2.7952	(2.28)
cil/ta					4.3085	(0.80)	3.2424	(0.59)
absgap					−4.7469	(−2.25)	−4.6843	(−2.29)
liquid					3.4007	(0.74)	3.1728	(0.71)
R^2	0.6966		0.7046		0.7117		0.7230	
N	1148		1148		1148		1148	

This table reports the estimation results of fixed-effect regressions on a 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. The dependent variable is the non-performing mortgage loans of the banks in a given quarter. The definitions of variables and details of the model estimation are provided in the article. Adjusted *R*-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

bank discriminates its borrowers significantly more than the *NS* bank for the same set of observable characteristics of the borrowers. Therefore, loan rates charged by the *S* bank will have a wider distribution than the loan rates charged by the *NS* bank for observationally equivalent borrowers. 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 in line with 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, these data are reported for very high-risk borrowers only; i.e., for the subset for which the effect of lax screening is potentially higher. We first estimate the following model of loan spread to parse out the effect of observable characteristics:

$$rate_{ib} = \alpha + \beta X_{ib} + \epsilon_{ib}.$$

$rate_{ib}$ is the log 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 the 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,

Table 8
Shrinkage in loan spread

	Panel A: All Banks			Panel B: Matched Sample		
	High OTD	Low OTD	Shrinkage	High OTD	Low OTD	Shrinkage
Standard Deviation	0.2236	0.2621	0.0385	0.2056	0.2627	0.0571
P75-P25	0.3144	0.3559	0.0415	0.2731	0.3669	0.0938
P90-P10	0.5697	0.6767	0.1070	0.5172	0.6883	0.1711
Bartlett's *p*-value			0.0001			0.0001
Levene's *p*-value			0.0001			0.0001

This table provides the dispersion in loan spread across high- (above-median) and low- (below-median) OTD banks. Panel A is for all banks, and Panel B for the matched sample. We provide three measures of dispersion in log loan spreads: standard deviation, the difference between the 75th and 25th percentiles, and the difference between the 90th and 10th percentiles. Shrinkage measures the difference in dispersion across the high- and low-OTD banks. Bartlett's and Levene's *p*-values are 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.

improvement, or refinancing), loan type (conventional or Federal Housing Administration (FHA)-insured loan), indicator for the state of the property, and the 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 bank's asset size (log of assets), liquidity ratio, maturity gap, CIL loans to total asset ratio, and the ratio of mortgage loans to total assets. These variables are included to control for bank-specific effects in pricing such as the bank's cost of capital and relative advantage in making mortgage loans.[16]

We are interested in the dispersion of the residual of this regression; i.e., ϵ_{ib}. Our hypothesis is that the high-OTD banks did not incur resources in discriminating across borrowers with similar observable quality but with different unobservable signals. ϵ_{ib} captures the effect of such unobservable factors. We compute three measures of dispersion in ϵ_{ib}: (1) standard deviation; (2) difference between the 75th and 25th percentiles; and (3) difference between the 90th and 10th percentiles. Table 8 reports the results. Panel A presents results for all banks, whereas Panel B is for the matched sample used in subsection 3.1. 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- (above-median) OTD banks is about 17–28% lower than the low- (below-median) OTD banks. We observe similar patterns for other two measures of dispersion as well. 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. Levene's test statistics for the equality of variance produce similar results. The Kolmogorov-Smirnov test statistic strongly rejects the equality of the two distributions as well.

16 We have experimented with several other reasonable specifications and obtained similar results. We report results based on one of the most comprehensive models to isolate the effect of observable information on loan spreads.

Overall, we show that the low-OTD banks offered loans at more discriminating terms for the same observable characteristics as compared with 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.

4. Capital and Liability Structure

We have so far established a link between OTD lending and the banks' screening incentives. Going forward, it is important to understand the characteristics of banks that engaged in such behavior. We do so by analyzing the effect of a bank's liability structure on the quality of OTD loans that it originated in the pre-disruption period. These tests serve two purposes. First, they allow us to sharpen our basic test that relates OTD lending to screening incentives. Second, they provide useful guidance for policy reforms that are aimed at deterring such behavior in the future.

4.1 Effect of capital constraints

As discussed earlier, the OTD model of lending has several advantages. By de-linking the origination of loans from their funding, banks can capitalize on their comparative advantage in loan origination without holding a large capital base. The benefit can be especially high for banks with a lower capital base because these banks are more likely to reject the loan application of a potentially creditworthy borrower due to regulatory capital constraints. The OTD model of lending allows these capital-constrained banks to provide credit to such marginal creditworthy borrowers. Thus, the securitized loans of such capital-constrained banks are likely to be of better quality than the securitized loans of unconstrained banks that face a similar set of borrowers.

In contrast, capital-constrained banks have lower screening and monitoring incentives (see Thakor 1996; Holmstrom and Tirole 1997) due to the well-known risk-shifting problem (Jensen and Meckling 1976). If banks are using the OTD market to create riskier loans by diluting their screening standards, then capital-constrained banks are predicted to have higher incentives to make inferior loans. Thus, we have sharply different predictions on the effect of capital constraints on the extent of mortgage defaults by high $preotd$ banks: one consistent with the sound economic motivation to economize on regulatory capital, and the other consistent with diluted screening incentives. We estimate the following triple-differencing model to test this prediction:

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

The dependent variable, $default_{it}$, measures the mortgage default rate of bank i in quarter t. cap_i measures the tier-one capital ratio of bank i during the

Table 9
The effect of bank capital

	All Banks				Excludes Large Banks			
	Model 1 NPA		Model 2 NPA		Model 3 NPA		Model 4 NPA	
Dependent Var:	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
after	0.2390	(1.06)	−0.6064	(−2.16)	0.1240	(0.51)	−0.7314	(−2.43)
*after*cap*	0.8111	(0.45)	0.9272	(0.55)	1.4960	(0.76)	1.8426	(1.01)
*after*preotd*cap*	−5.4985	(−2.05)	−5.2733	(−2.01)	−5.1978	(−1.89)	−5.2544	(−1.93)
*after*preotd*	1.1495	(2.49)	1.0360	(2.31)	1.0716	(2.25)	1.0056	(2.16)
*after*premortgage*	0.6313	(1.17)	0.8177	(1.56)	0.4066	(0.78)	0.6109	(1.16)
logta	0.2335	(0.53)	0.3191	(0.75)	0.7031	(1.45)	0.7281	(1.48)
cil/ta	2.5588	(1.34)	2.8332	(1.45)	2.2419	(1.12)	2.5009	(1.22)
liquid	1.3795	(0.91)	1.3492	(0.95)	−0.1292	(−0.12)	−0.1240	(−0.11)
absgap	−3.2334	(−3.81)	−3.0484	(−3.69)	−3.1012	(−3.61)	−3.0050	(−3.51)
*after*li*			0.2714	(2.64)			0.2827	(2.63)
*after*highrate*			1.9064	(3.85)			1.6838	(3.67)
*after*noincome*			0.6671	(2.42)			0.5810	(1.87)
R^2	0.7303		0.7340		0.7140		0.7160	
N	5397		5327		4977		4907	

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

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

The dependent variable, $default_{it}$, is measured as the ratio of non-performing mortgages to 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; cap_i is bank i's average tier-one capital ratio 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 assets ratio; *absgap* is the absolute value of one-year maturity gap as a fraction of total assets. li measures the average loan-to-income ratio of all loans issued by the bank in 2006. $highrate$ measures the fraction of high-interest-rate loans originated by the bank, and $noincome$ measures the fraction of loans without income documentation originated by the bank in 2006. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

pre-disruption quarters. We take the average value of this ratio for the pre-disruption quarters (2006Q3 to 2007Q1) to capture the effect of the capital ratio at the time these loans were made. Table 9 provides the estimation results. Consistent with our earlier analysis, we present results for both the "All Bank" sample and the "Excluding Large Banks" subsample. In Models 1 and 3, we estimate the regression model with bank-level control variables only. Models 2 and 4 control for borrower characteristics based on the HMDA dataset for 2006.

It is important to note that banks choose their capital ratios endogenously. This raises a potential concern for our identification strategy in this section. For example, consider a bank CEO who prefers higher risk for some unobserved reasons. A bank with such a CEO is likely to keep lower capital and at the same time originate riskier loans in the OTD market. Our triple-difference tests exploit variations within the set of high-OTD banks. Said differently, the coefficient on the triple-interaction term measures the incremental effect of capital constraints, holding fixed the level of OTD loans. The unconditional effect of capital constraint is captured by the double-interaction term $after * cap$. The test design, therefore, minimizes the endogeneity concerns to a large extent. In addition, Models 2 and 4 control for borrowers' risk characteristics, which further alleviates the concern regarding the endogeneity of bank capital.

We find a positive and significant coefficient on $after * preotd$ in all specifications, confirming our earlier results that banks with higher-OTD loans in the pre-crisis period experienced larger defaults on their mortgage portfolios in the post-crisis quarters. The coefficient on $after * cap$ is positive but insignificant. The coefficient on the triple-interaction term; i.e., the coefficient of interest, is negative and statistically significant. Thus, the effect of OTD lending on mortgage default rate weakens for banks with a higher capital base. In other words, the relationship between OTD lending and mortgage default rate is predominantly concentrated among banks with lower capital. A one-standard-deviation decrease in the capital ratio translates into 0.18% higher defaults, which is about 13% of the sample median of mortgage default rates. This result shows that banks used the OTD channel mainly to originate poor-quality loans rather than to save on regulatory capital. The result, therefore, is consistent with the dilution in screening standards of the high-OTD banks.

4.2 Effect of demand deposits

We study the effect of demand deposits on the quality of OTD loans in order to further understand the role of funding structure on the banks' lending behavior. We focus on demand deposits because their presence is one of the defining features of commercial banks (see Diamond and Dybvig 1983). There are two economic forces leading to opposite predictions about the role of demand deposits on a bank's lending behavior. While the presence of subsidized deposit insurance might encourage banks with a large demand deposit base to engage in imprudent risk-taking behavior, the fragility induced by demand deposits can also act as a disciplining device. The threat of large-scale inefficient withdrawal by the depositors can exert an ex ante pressure on the bank managers' risk-taking behavior. Calomoris and Kahn (1991) and Flannery (1994) provide theoretical arguments that demand deposits can control imprudent risk-taking activities of a bank. Diamond and Rajan (2001) show that the demand deposits can act as a disciplining device by committing the banker to avoid undesirable risky behavior. The franchise value associated with a large deposit base might limit a bank's risk-taking behavior as well.

We examine the role of demand deposit on risk-taking through the OTD model of lending using the same empirical methodology that we use for the test involving the effect of capital ratios. We estimate a triple-differencing model and provide results in Table 10. We measure the extent of dependence

Table 10
The effect of demand deposits

	All Banks				Excludes Large Banks			
	Model 1 NPA		Model 2 NPA		Model 3 NPA		Model 4 NPA	
Dependent Var:	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
after	0.5045	(3.66)	−0.2957	(−1.38)	0.4479	(3.00)	−0.3404	(−1.52)
*after*dd*	−1.6465	(−2.43)	−1.6697	(−2.44)	−1.3884	(−1.98)	−1.4100	(−2.02)
*after*preotd*dd*	−3.9949	(−2.34)	−3.7627	(−2.25)	−3.4250	(−2.09)	−3.2896	(−2.04)
*after*preotd*	0.9364	(2.79)	0.8260	(2.58)	0.8294	(2.52)	0.7423	(2.32)
*after*premortgage*	0.5526	(1.04)	0.7312	(1.43)	0.3507	(0.68)	0.5570	(1.07)
logta	0.2222	(0.51)	0.3085	(0.74)	0.6675	(1.39)	0.6942	(1.42)
cil/ta	2.7117	(1.44)	3.0167	(1.57)	2.4083	(1.21)	2.7033	(1.34)
liquid	1.3462	(0.92)	1.3215	(0.97)	−0.0527	(−0.05)	−0.0373	(−0.03)
absgap	−3.2555	(−3.91)	−3.0656	(−3.78)	−3.1305	(−3.70)	−3.0252	(−3.60)
*after*li*			0.2548	(2.53)			0.2648	(2.51)
*after*highrate*			1.9479	(4.07)			1.7502	(3.89)
*after*noincome*			0.6255	(2.33)			0.5534	(1.83)
R^2	0.7322		0.7358		0.7154		0.7173	
N	5397		5327		4977		4907	

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

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

The dependent variable, $default_{it}$, is measured as the ratio of non-performing mortgages to 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; dd_i is bank i's average demand deposits to total deposits ratio 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 assets ratio; *absgap* is the absolute value of one-year maturity gap as a fraction of total assets. li measures the average loan-to-income ratio of all loans issued by the bank in 2006. $highrate$ measures the fraction of high-interest-rate loans originated by the bank, and $noincome$ measures the fraction of loans without income documentation originated by the bank in 2006. Adjusted *R*-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

on demand deposits by taking the ratio of demand deposits to total deposits of the bank. The ratio is computed as the average over the pre-crisis quarters. The coefficient on the triple-interaction term $after * preotd * dd$ measures the incremental effect of demand deposits on the mortgage default rate of banks with a higher fraction of demand deposits.

In all specifications, we find a positive and significant coefficient on $after * preotd$ consistent with our base results. More notably, we find a significant negative coefficient on the triple-interaction term. As the fraction of demand deposits increases, the relationship between OTD lending and mortgage default rate weakens. A one-standard-deviation increase in the demand deposit ratio translates into a decrease of 0.24% in default rates, which is approximately 18% of the sample median of mortgage default rate. Overall, the results show that high-OTD banks that are funded primarily by demand deposits did not originate excessively risky loans. It is the set of high-OTD banks without heavy reliance on demand deposits that experienced disproportionately higher default rates in the immediate aftermath of the crisis. 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. These results are consistent with the view that demand deposits create an ex ante effect by limiting excessive risk-taking by the bank. In unreported tests, we include the effects of capital position and demand deposits together in the model and find that the results remain robust. Taken together, these results show that banks that were predominantly funded by non-demandable deposits or wholesale market-based sources of funds were the main originators of inferior-quality mortgages. These findings highlight the interdependence between a bank's funding structure and its asset-side activities (see Song and Thakor 1997). In particular, any regulation designed to address a bank's risk-taking behavior on the lending side should also focus on incentive effects generated by its liability structure.

5. Discussion and conclusion

We argue that the originate-to-distribute model of lending resulted in the origination of inferior-quality loans in recent years. Using a measure of banks' participation in the OTD market prior to the onset of the subprime mortgage crisis, we show that banks with higher OTD participation have higher mortgage default rates in the later periods. These defaults are concentrated in banks that were 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. Equally important, our study shows that these incentive problems are severe for poorly capitalized banks and banks that rely less on demand deposits. Thus, a 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. They provide useful inputs to the regulation of financial markets and the determination of capital ratio for the banking sector. Our results also imply that the probability of default of a mortgage depends on the originator of the loan in a predictable way. These findings can serve as important inputs to the pricing models of mortgage-backed securities.

Appendix: Variable construction from call report

We obtain data from quarterly call reports filed by FDIC-insured commercial banks.

- Liquid assets: We define liquid assets as the sum of cash plus federal funds sold plus government securities (U.S. treasuries and government agency debt) held by the banks. Note that we do not include all securities held by banks, since they also include 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 and NPA: We take net chargeoff (net or recoveries) on the residential 1–4 family mortgages. We consider all mortgage loans that are past due 30 days or more and loans that are delinquent as non-performing mortgages, or as mortgages under default.
- 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 filed 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 the 1–4 family residential mortgage market for two consecutive quarters. The first quarter in which banks reported this data item is 2006Q3. The data are 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. We compute the average value of this number based on 2006Q3, 2006Q4, and 2007Q1 to construct a bank-specific measure of participation in the OTD lending. If an observation is missing for any of these quarters, we compute the average value based on remaining observations.
- 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 the 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.
- Maturity gap: We construct a one-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 + Customer's 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 + Bank's Liabilities on Customer's Outstanding Acceptance. We take the absolute value of this number and scale it by the total assets of the bank to compute the one-year maturity gap ratio.

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