THE INCENTIVE STRUCTURE OF THE ORIGINATE-TO-DISTRIBUTE MODEL OF LENDING, BANK CREDIT SUPPLY AND RISK TAKING BEHAVIOUR OF U.S. COMMERCIAL BANKS

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Abstract

Traditionally, the fundamental business of banks is holding deposits and making loans. Until a few decades ago, banks used to hold loans until borrowers repaid them, because selling loan portfolios was too costly. This is called 'originate-to-hold'. Loan sale and securitization have changed the traditional banking framework from 'originate-to-hold' to 'originate-to-distribute' (OTD), which allows banks to sell or securitize loans rather than holding them on their balance sheets.

Our research investigates the incentives for using the OTD model of lending and its impact on bank credit supply and risk taking behavior based on involvements in the OTD model and different bank size. Data about OTD lending, balance sheet structure and risk characteristics are collected from Call Reports from 2006Q3 to 2009Q2. We first divide total banks into low-OTD and high-OTD banks based on their involvement in the OTD model. Using a Fixed Effects Model and a System Generalized Method of Moments (SGMM) panel methodology, we find strong evidence that both low- and high-OTD banks with more OTD mortgage loans tend to adopt the OTD model of lending. Poor performance of mortgage loans could be another driving force to use the OTD model. Besides that, high-OTD banks resort to the OTD model as an additional source of funding to finance loans and liquidity when they

face higher costs or liquidity constraints. Furthermore, the whole sample is divided into small and large banks based on the value of total assets. Our results are consistent with the regulatory arbitrage hypothesis and indicate that small banks seek to use the OTD model of lending to alleviate capital requirements as they are less-capitalized. Our results show that they are more likely to experience funding and liquidity shocks and meet their funding and liquidity needs through OTD lending.

Since banks use the OTD model as liquidity and funding provider, we want to investigate further its impact on bank credit supply. Our results indicate that it contributes to a significant increase in supply of credit, as suggested by a positive relationship between OTD lending and loan supply but not for low-OTD banks. However, we cannot find this positive effect during the crisis period since banks tended to hoard liquidity and were unwilling to make loans due to illiquid market conditions. In addition, we find evidence that OTD lending has changed the effect of monetary policy through the bank lending channel, as indicated by the positive effect of changes of monetary policy on bank lending.

Finally, the OTD model of lending has a beneficial impact in terms of credit supply to the economy but we also want to know whether it has a detrimental effect and examine its impact on bank risk taking. Our

results suggest that the OTD model has an adverse effect on bank riskiness for both low- and high-OTD banks. Moreover, small banks seem to be more risky and less stable since they are more highly involved in the OTD model relative to large banks. Our findings suggest that OTD loans originated during the pre-crisis period mainly contribute to an increase in default rate and net-charge-offs, making banks less stable.

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Abbreviations

ABS	Asset-Backed Securities
ABB	Asset-Backed Bond
ABCP	Asset-Backed Commercial Paper
AIG	American International Group, Inc.
ARM	Adjustable-Rate Mortgage
BHC	Bank Holding Company
CAR	Capital Asset Ratio
C&I	Commercial and Industry Loans
CLO	Collateralized Loan Obligation
CMO	Collateralized Mortgage Obligation
CRA	Credit Rating Agency
CRT	Credit Risk Transfer
DGMM	Difference Generalised Method of Moments
DTI	Debt to Income
Fannie Mae	Federal National Mortgage Association
FE	Fixed Effect
FHA	Federal Housing Administration
FmHA	Farmers Home Administration
Freddie Mac	Federal Home Loan Mortgage Corporation

FRM	Fixed-Rate Mortgages
GDP	Gross Domestic Product
Ginnie Mae	Government National Mortgage Association
GMM	Generalised Method of Moments
GSE	Government Sponsored Entity
HELOC	Home Equity Line of Credit
HMDA	Home Mortgage Disclosure Act
HPI	House Pricing Index
HUD	Department of Housing and Urban Development
LDV	Lagged Dependent Variable
LPS	Loan Portfolio Servicing
LTV	Loan-to-Value
MBS	Mortgage-Backed Securities
NPL	Non-Preforming Loan
OTD	Originate to Distribute
PMI	Private Mortgage Insurance
REMIC	Real Estate Mortgage Investment Conduit
REIT	Real Estate Investment Trust
RMBS	Residential Mortgage Backed Securities
ROA	Return on Assets
SGMM	System Generalised Method of Moments
SPV	Special Purpose Vehicle

VA	Veterans Administration

Chapter 1

Introduction

1.1 Background and Motivation

Historically, the fundamental business of banks is holding deposits and making loans. On the liabilities side of the balance sheet, depositors save money with banks and withdraw money when required. Meanwhile, banks make loans to borrowers, who promise to repay based on debt contracts, and banks hold these loans on the assets side of their balance sheets. It has been costly for banks to sell their loan portfolios and they have held loans until the borrowers repaid. This is called originate-to-hold. Competitive pressure and increased capital requirements have limited banks' profits from this area, leading them to seek other profitable business. As regulators loosened regulation, banks participated in wider activities and financial innovations emerged during the second half of the last century. The development of financial innovations, loan sale and securitization, has led to a fundamental change in the bank business model. A new business model, the originate-to-distribute (OTD) model, allows banks to sell loans to third parties rather than holding them until maturity on their balance sheets. Two important fundamental functions of banks have been changed by the OTD model: liquidity transformation (Diamond and Dybvig, 1983) and delegated monitoring (Diamond, 1984). As banks are able to offload loans from balance sheets, they rise funding through selling loans to finance loans and liquidity (Diamond and Rajan, 2001; Loutskina and Strahan, 2009; Loutskina, 2011). Thus, banks are less dependent on their traditional source of funding. In addition, banks have lower incentives to monitor borrowers after selling off loans from balance sheet (e.g. Pennacchi, 1988; Gorton and Pennacchi, 1995; Keys et al., 2010; Purnanandam, 2011).

There is a growing literature about the benefits for banks to participate in the OTD model. The OTD model allows them to reduce expected regulatory costs (Pennacchi, 1988), lowering the cost of capital by saving reserves to meet capital requirements set up by regulators (James, 1988; Gorton and Pennacchi, 1995). This business model also provides an additional source of funding to finance loans and liquidity (Loutskina, 2011). Banks can transfer risk from the banking system to other sectors in order to improve risk sharing, since loans can be sold to the rest of economy (Allen and Carletti, 2006). Unfortunately, any positive effects have been tarnished by the high default rate suffered by securitized products created under the OTD model since 2007. The negative effects predominate after the financial crisis due to distortion of incentives.

Studies have started to question the OTD model and the actual role played by OTD model; thus it is very important to know why banks tend to be engaged in the OTD model. Our work is related to several others (Bedendo and Bruno, 2012; Affinito and Tagliaferri, 2010; Mantin-Oliver and Saurina, 2007; Bannier and Hänsel, 2007; Uzun and Webb, 2007) that examine why banks want to securitize loans in the process of securitization, we extend their work by examining this issue at the frontend of securitization.[1] Thus, we seek to understand the incentives for banks to engage in OTD lending. Moreover, we update their work by dividing banks based on different intensities of involvement in the OTD model. This is important because banks with different levels of involvement in the model might have different incentives to use the OTD model of lending. Finally, we also extend the research period to the peak of the crisis and its aftermath and examine to what extent use of the OTD lending changed after the crisis, since the literature mainly focuses on the motivations for using OTD lending during the pre-crisis period (Affinito and Tagliaferri, 2010; Mantin-Oliver and Saurina, 2007; Bannier and Hänsel, 2007) and has scarcely discussed this issue after the financial crisis.

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[1] Uzun and Webb (2007) compare securitized and non-securitized US banks to study why banks securitize their loans.

Furthermore, our research is linked to recent literature that has intensively discussed the impact of securitization on the supply of loans. Banks tend to decrease lending standards and lend to more risky borrowers after they have sold loans from their balance sheets, leading to an expansion of aggregate credit supply (Dell' Ariccia and Marquez, 2006; Demyanyk and Hemert, 2009). Mian and Sufi (2008) demonstrate evidence of credit expansion in high latent demand zip codes driven by securitization using loan-level data. In addition, Altunbas et al. (2009) show that European banks that are highly involved in securitization also tended to be more willing to make loans during the period between 1999 and 2005. Our research examines further whether OTD lending has a positive impact on loan growth by using bank-level data rather than loan-level data at the frontend of securitization, since it provides a source of funding and liquidity. In particular, it is necessary to investigate whether it has a disparate effect on supply credit based on levels of involvement in the OTD model since only high-OTD banks seek to use the OTD model to finance loans and liquidity (based on our previous findings). It is also suggested by Bedendo and Bruno (2012) that securitization can provide liquidity and increase loan supply during the financial downturn and that is why Federal Reserve banks try to preserve liquidity of the securitization market in response to unexpected adverse shocks. We extend their work and examine whether OTD lending can contribute to a significant supply of credit after the financial crisis vary across different degrees of involvement in the OTD model and bank size.

Another stand of the literature studies the effect of OTD activities on bank lending in the event of adverse shocks. Loutskina and Strahan (2009) argue that the OTD model allows banks to be less dependent on a lenders' financial conditions, increasing their willingness to provide credit. It also can shelter banks from the effect of monetary policy through the bank lending channel (Altubas et al., 2009). This is consistent with Loutskina (2011) who suggests that the model allows banks to be less sensitive to adverse costs of funding shocks, reducing the effectiveness of tightening monetary policy. Our study updates the literature and examines whether OTD lending has changed the link between the changes of monetary policy and loan supply based on different levels of involvement in the OTD model and bank size. This might be due to different responses to the impact of the OTD model on bank lending following changes in monetary policy.

Since we examine the positive effect of OTD lending in terms of credit supply to the economy, we are also interested in assessing whether it has a detrimental effect on bank stability. In general, previous studies suggest that there is a positive relationship between the OTD model and bank risk taking behavior. Since securitization allows banks to convert illiquid assets into liquid funds, it enables them to lend to riskier borrowers and increases credit supply. It is argued that banks tend to decrease lending standards and lend to more risky borrowers, triggering a deterioration of loan portfolios (Dell'Ariccia and Marquez, 2006; Dell' Ariccia et al., 2010). Mian and Sufi (2009) use zip-code level information to examine the impact of securitization on default rate and they find that regions with an excessive credit supply in high latent demand zip have a higher rates of default. In addition, some theoretical studies suggest that banks lower incentives to monitor borrowers after selling loans from their balance sheets (Parlour and Plantin, 2008; Bubb and Kaufman, 2009). There is empirical evidence that banks active in the OTD model have relatively higher default rates due to lower incentives of monitoring. Keys et al. (2010) argue that securitized mortgage loans around FICO score 620 have higher default rates than those retained on the balance sheet due to lack of monitoring. Purnanandam (2011) also finds that banks that participated intensively in the OTD model before the crisis have lower screening incentives, suffering a higher default rate in mortgage loans and higher mortgage charge-offs in the post-disruption period.

In contrast, using US Bank Holding Company (BHC) data from 2001 to 2007, Jiangli and Pritsker (2008) examine the impact of mortgage securitization on insolvency risk by taking into account that banks securitize assets back onto their balance sheets upon default and find that the OTD model plays a positive role in reducing insolvency risks.[2] Consistent with Jiangli and Pritsker (2008), Casu et al. (2011), using BHC data from 2001 to 2007, argue that banks with larger amounts of outstanding securitized loans are more risk-averse and tend to choose loan portfolios with lower credit risk. Thus, the previous studies suggest that the net impact of the OTD model of lending on the risk-taking behavior of banks is ambiguous and our research extend their work to clarify whether intensive engagement in the OTD market has a detrimental effect on bank stability at the frontend of securitization. More importantly, we examine whether the impact of the OTD model varies across banks with different degrees of involvement in the model and across bank size. This may be because the OTD lending may different in its effects on bank risk taking across these groups. In addition, our research diverges from those recent papers which mainly focuses on the impact of OTD activities on bank risk before the financial

[2] Banks sell originated OTD loans with an exposure to credit risk by providing an implicit guarantee with SPV that banks will back their non-performing loans to balance sheet. Furthermore, originators usually promise to repurchase the tranche with worst credit (known as equity tranche) from SPV to increase credit enhancements.

crisis and we update the work by extending research period until the peak of the crisis and study this impact including post-crisis period.

1.2 Research Objectives

The aims of this study are:

1) To investigate the incentives for banks to engage in the OTD model of lending.
2) To examine the effect of OTD lending on the supply of loans and identify the role that OTD lending plays in the transmission of monetary policy through the bank lending channel.
3) To identify the impact of the OTD model on bank risk-taking behaviour.

We examine the incentives for OTD lending in banks with different degrees of involvement in the model. We divide banks into two groups, low- and high-OTD banks based on the average OTD ratio. We also divide banks into small and large banks based on the value of total assets to investigate whether these two groups have similar incentives to engage in OTD lending. Moreover, we want to study its use during the financial downturn, so we incorporate a time dummy to insulate OTD activities during the pre-crisis period and use the interaction term OTD lending and a time dummy to examine whether banks can use OTD lending during the financial turmoil. To achieve those objectives, we address the following three questions: What motivates banks to be engaged in the OTD lending for low- and high-OTD banks? Do small banks and large have similar incentives to use OTD model of lending? Can banks use the OTD model of lending during the financial crisis?

The next objective is to investigate the impact of OTD lending on credit supply. In particular, we examine this effect based on banks' involvements in the OTD model of lending and bank size. We also want to study its impact on the supply of loans changed during the crisis period. In addition, we examine the interaction between OTD lending and changes of monetary policy to shed more light on the effects of OTD lending on changes in monetary policy through the bank lending channel. To address these objectives, we then ask four questions as follows: Does OTD lending lead to a significant increase in loan supply in both low- and high-OTD banks? Do small banks and large banks that are active in OTD lending show a significant increase in loan growth? To what extent did the impact of OTD lending on the credit supply change during the financial crisis? How does OTD lending affect bank lending in the context of changes in monetary policy?

The finial research objective is to investigate whether OTD lending contributes to an increase in bank risk. This addresses four questions:

How does the OTD model of lending affect bank risk taking for both low-OTD and high-OTD banks? Does OTD lending have different effects on the risk-taking of small and large banks? To what extent is bank risk affected by stuck loans which cannot be sold off from balance sheets? How does OTD lending affect portfolio risk and leverage risk of banks?

1.3 Thesis Structure

This thesis is organized as follows. Chapter 2 introduces background knowledge of loan sale and securitization developed under the OTD model. Chapter 3 reviews theoretical and empirical studies related to the research. Specifically, we review the literature on the motivations of OTD lending and its impact on the credit supply and bank risk-taking. Data collection, sample selection and methodology are in the Chapter 4. In Chapter 5, we examine the determinants of OTD lending varying across banks with different intensities of involvement in the OTD model and bank size and whether its role has changed under the financial crisis. Chapter 6 examines the impact of the OTD model on credit supply and its effect on the bank lending channel following changes in monetary policy. Chapter 7 studies the impact of OTD lending on bank risk based on banks' involvements in the OTD model and bank size. Finally, contributions, policy implications and conclusions of the thesis and proposed future research are in Chapter 8.

Chapter 2

Introduction to the Originate-to-Distribute (OTD) Model

2.1 Introduction

In a traditional bank lending model, banks hold loans until borrowers repay them which is called originate-to-hold. There has been a dramatic increase in the loan sales and securitization during recent decades, leading to a fundamental change of bank business model. A newer model, Originate-to-Distribute (OTD), allows banks to sell and securitize loans rather than holding them until maturity. In this chapter, we introduce the OTD model. In section 2.2, we discuss the process of securitization and key players in the process of securitization. Since we focus on the OTD lending of mortgage loans, we include more details about mortgage securitization in section 2.3. In this section, we provide an overview of two different ways to securitize mortgage loans, either though GSEs or through private entities. Section 2.4 summarizes mortgage securitization in the prime and subprime market. Finally, we review trends for the OTD model in section 2.5.

2.2 The OTD Model and Securitization

2.2.1 The Process of Securitization

Securitization enables a bank to transform illiquid assets into marketable securities. It involves selling loans, repackaging them into a securitization pool and then issuing securities backed by these loans. Several classes of assets have been securitized, such as residential multifamily, commercial mortgage loans, automobile loans, credit card receivables, small business administration loans, computer and truck leases, loans form mobile homes, and various finance receivables. The general securitization process includes two steps: pooling and tranching (Gorton and Souleles, 2006). Figure 2.1 depicts the process.

In the first step, originators make loans then sell them with underlying cash flows to the securitization pool. Loans purchased from banks and other lenders are pooled together into diversified portfolios. After pooling assets, arrangers sell the pool to a separate legal entity known as a special purpose vehicle (SPV) which is managed by arrangers for investors. Since cash flows from assets are sold to SPVs, the pool of purchased assets can be financed by arrangers issuing securities in the capital market. If arrangers are depository institutions, such as banks, they can use their own internal funds to finance the pool. Otherwise, funding from a warehouse lender is required by arrangers until loans can be sold ("warehouse" by analogy with storage of physical goods, until sold).

The second step of securitization is when SPVs issue debt securities backed by the pool of assets and sell them to investors. In this case, assets in the pool are regarded as collateral that guarantee payments on securitized mortgages. Securities issued by SPVs are tranched with different priority claims against the underlying assets. Tranches of securities are designed and sold to different types of investors to cater to their risk preferences. A credit rating agency (CRA) is responsible for assigning a credit rating to these tranches, based on their own criteria (see, for example, Ashcraft and Schuermann, 2008). The top tranche, known as the "super senior tranche", has the lowest default risk and receives the highest rating (from well-known agencies such as Standard & Poors or Moodys). It has relatively low return but will be the first to be paid out. The unrated "equity tranche" or ("toxic waste") is the last to be paid and so is most likely of all the tranches to suffer loss if mortgages in the pool fail to pay. The mezzanine tranche lies between these two tranches. In general, banks tend to sell more senior tranches to investors and retain lower tranches, giving incentives to banks to expend efforts to monitor borrowers.

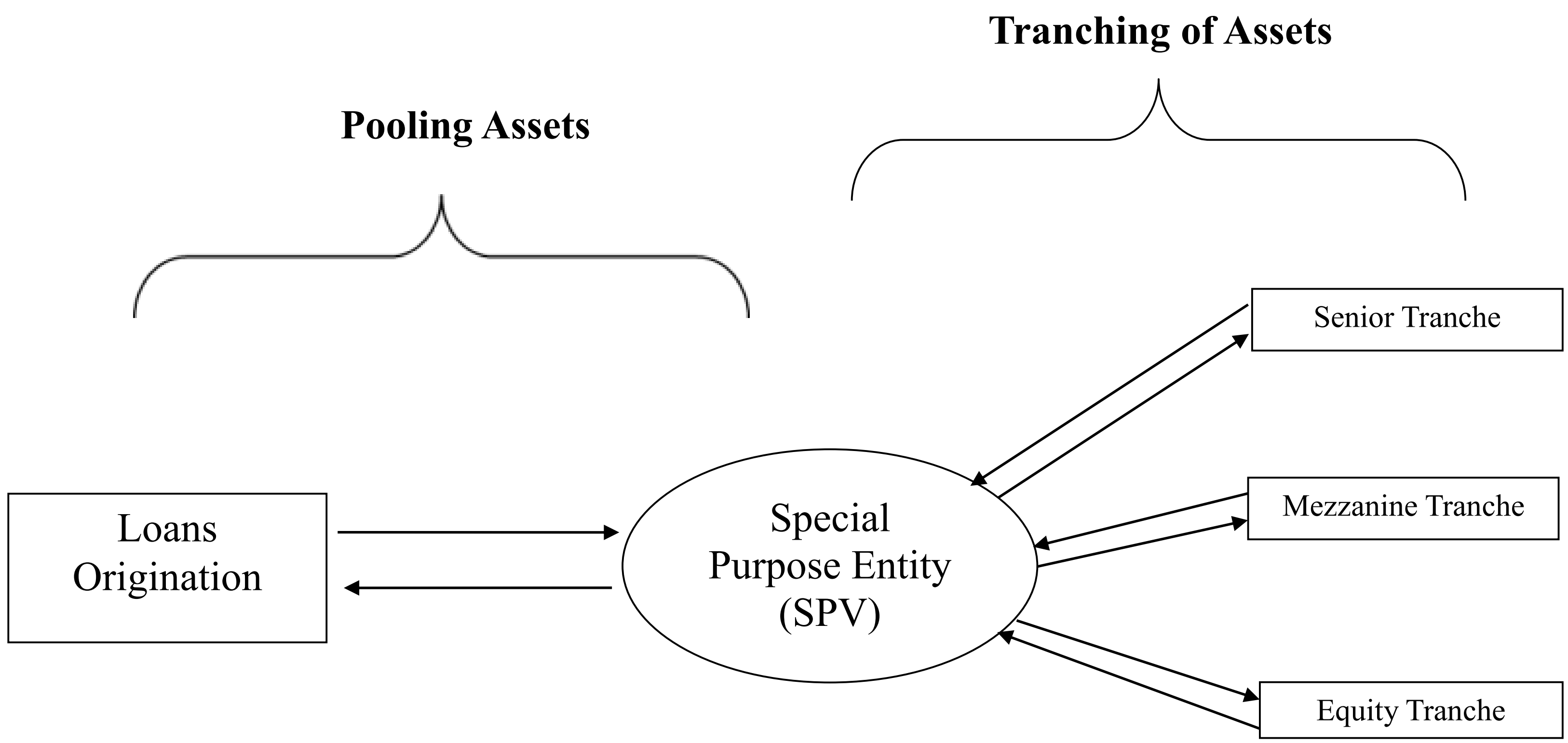

Figure 2.1: The process of securitization Source: Gorton and Souleles (2006)

2.2.2 Key Players in the Process of Securitization

There are six key participants in the process of securitization (see Figure 2.2). The loan originator can be a bank or a thrift which makes loans to borrowers. Generally, the originator also services loans after they have been sold off from the balance sheet, collecting payments and ensuring that the borrower meets his obligations to repay and collecting payments on the securitized loans. Only a few commercial banks have the ability to securitize loans and most banks sell pool of loans to arrangers or issuers. Loans may be sold several times before entering into a securitization pool.

The SPV is created by an issuer or arranger though transferring assets. It is usually thinly capitalized and has no independent management or employees. There are no other decisions to be made in the SPV and a trustee performs an administrative role by the receipt and distribution of cash. In the process of securitization, an SPV is a legal form of a trust which is structured to be bankruptcy-remote and tax neutral (Gorton and Souleles, 2006). It is set up solely to purchase loans from the originator and issue securities to investors. Before transferring loans to the SPV, loans with similar features have been pooled together and are collateral guaranteeing payments on securities against underlying assets. Since cash flows from loans are sold to SPVs with the proceeds, the pool of purchased assets can be financed by arrangers issuing securities in the capital market. Since an SPV is a trust with independent bankruptcy, selling loans to the trusts allows both originators and arrangers to protect themselves from losses on mortgage loans. In order to obtain off-balance sheet treatment for the SPV, the asset transfer needs to be treated as a "true sale" (Gorton and Souleles, 2006).[3]

Since there is an adverse selection problem between arrangers and investors due to information advantages about loan quality, the arranger has an incentive to sell bad loans and retain good ones. In order to mitigate the problem that a shortfall of cash flow in the SPV is below the amount which is obligated to pay investors, credit enhancements and liquidity enhancements are provided by a credit enhancer to guarantee payments to investors and reduce the credit risk of payment receivables. The credit enhancer provides the SPV with explicit or implicit resources as credit enhancements. The most common way of providing an explicit recourse is to retain partial interests in the transferred assets by tranching securities to make a subordination structure according to probabilities of default of underlying borrowers. The most senior tranches and junior or mezzanine tranches, which are called A notes and B notes respectively,

[3] Financial Accounting Standard No. 140 (FAS 140) sets two general requirements for a true sale. One is that the SPV must be a "qualifying" SPV (QSPV). The other one is that sponsor must surrender control of the financial assets.

tend to be sold in the capital market, whereas the most junior securities, named C notes, are typically privately placed and may be retained in the SPV. Some other forms of credit enhancement include over-collateralization, excess spread (cash flow from underlying assets), and collateral interest. In addition, third parties provide credit enhancements, such as letters of credit, surety bonds and other instruments.[4] Meanwhile, the liquidity enhancer provides backup cash to make sure that investors will receive principal and interest on time. The guarantees of highly rated credit enhancers are added to the bundle of rights purchased by investors to protect them from losses.

Credit rating agencies (CRAs) are responsible for giving credit ratings based on their own criteria (Ashcraft and Schuermann, 2008). Investors do not have time to analyze these securities and make investment decisions mainly based on the ratings which are given by CRAs. In general, the lower the probability of default, the higher rating securities have. Thus, the most senior tranches usually have a higher rating than other tranches. In order to get higher rating, different forms of internal credit enhancements from the originating bank and external credit enhancement are given by third parties, as noted earlier.

[4] Ashcraft and Schuermann (2008) provide a detailed discussion about several forms of credit enhancements in subprime mortgage securitization.

Servicers are sometimes employed by arrangers to offer service related to originated loans, such as the collection of loan payments, in return for a service fee paid by the SPVs. As noted, originators usually service loans to make sure borrowers meet their obligations but sometimes originator and servicer are not the same institution. When an arranger wants to issue securities, the underwriter or an investment bank gets involved to help issue securities and is responsible for pricing and marketing the securities to investors. Finally, investors play a vital role in the success of securitized markets. They will receive loan interest and principal payments though servicing firms. In general, institutional investors are more likely to purchase these securities, such as insurance companies, pension funds, mutual funds and sometimes individuals.

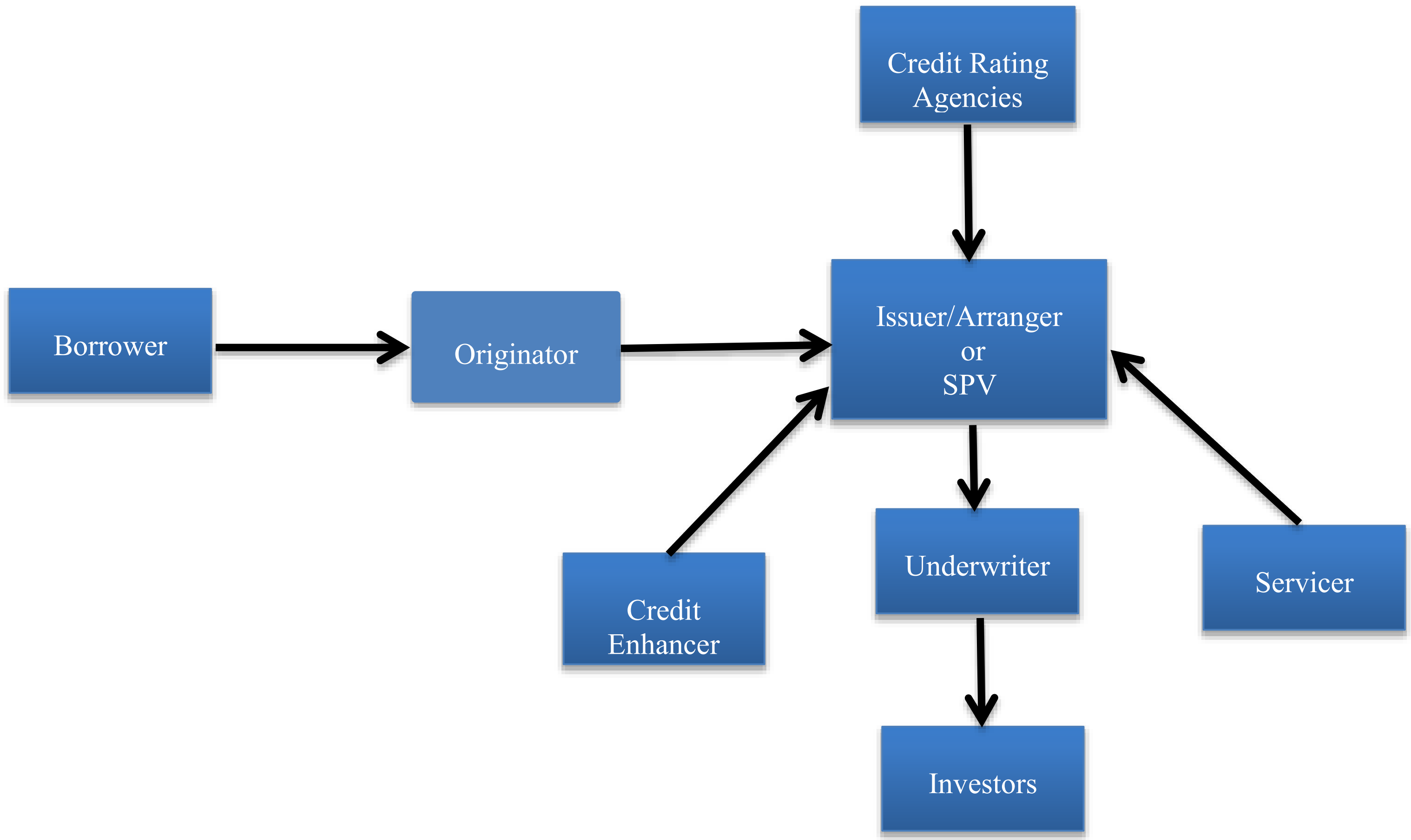

Figure 2.2 Key players in the process of securitization

2.2.3 Different Types of Securitization Contracts

There are three types of securities backed by underlying loans. The first type is pass-through, which represents direct ownership in the portfolio of loans (mortgages) with similar maturity, interest rate and quality characteristics. This means that all contracts are similar to investors in the pass-through and investors will receive exactly the same principal and interest cash flows which are guaranteed from mortgage loans in each month. The portfolio is sold to a trust and issues claims against the entire loan portfolio, sold directly to investors. In general, the loan originator or servicer collects principal and interest on the mortgage loans and deducts the fee before passing along to the investors. The pass-through does not appear on the originator's balance sheet since claims are sold to investors. There are two different structures in the pass-though: static pool and dynamic pool.

Static pool refers to the pool of loan portfolios against claims sold to investors being fixed. Repayments from borrowers are paid to a separate interest-bearing account known as a collection account. Payments from this account are used to pay the servicing fee first and then the trustee passes along monthly payments of principal and interest to investors. A credit enhancement is provided through over-collateralization or an insurance bond purchased (insurance fee paid to credit enhancer) by the originator and is used to make up shortfalls in the case of mortgage default. However, it only can cover losses on some proportion of the loan portfolio. Gorton and Souleles (2005) note that about 10-15 percent of the value of a securitized loan portfolio can be covered, which means the credit enhancer is only responsible for covering losses up to the percentage of the loan portfolio specified.[5] Ginnie Mae is the most common type of static pass-through, which is an MBS collateralized by FHA-VA mortgages. Dynamic pool means that the mortgage loans included in the pool against claims sold to investors are usually short term and the compositions of loan portfolios can be changed. The average maturity of mortgage loans included in a pool is shorter than the maturities of claims against the pool, which is referred to as a "revolving structure". During this period, only interest is paid to debt holders. Principle is reinvested and not paid until the end of the revolving period. This approach is most commonly used in credit card receivables.

The second type is the asset-backed bond (ABB), which is also collateralized by a portfolio of loans. Unlike the pass-through, underlying assets against ABBs are sold to a financial company which is a subsidiary owned by the originator for the purpose of securitization

[5] In order to cover loan defaults, the credit enhancer usually purchases default contracts and the payments from a credit enhancer are received to cover the losses up to specified percentage of the value of loan portfolios.

and, thus, the assets remain on the originator's balance sheet. Another difference between ABBs and pass-through is that the subsidiary issues its claims to investors usually with the help of the underwriter (an investment bank), rather than selling assets to a trust and then issuing claims. The principle and interest payments are collected by the financial company and are transferred to the trustee, but cash flows from underlying assets are not dedicated to paying principal and interest on ABBs. In general, ABBs are created through over-collateralization; collateral against these securities is regularly evaluated to check whether their value falls below the amount stated.

The third type of securitization contracts is the pay-though bond. The Collateralized Mortgage Obligation (CMO) is a common example of pay-though bond, first issued by Freddie Mac in 1983. It combine features of both the pass-though and the ABB. Like the pass-through, cash flows collected from underlying assets against bonds are used to pay bondholders but the assets remain on the balance sheet of the originator. Each CMO is divided into three tranches and each tranche can receive interest rate semi-annually, but the principal payments are strictly prioritized and scheduled. On the top of this tranche structure, bondholders of tranche A have priority to be paid off. Tranche B starts to receive principal payments until bondholders of tranche A completely are paid off. Then tranche C bondholders can receive payments and prepayments after bondholders of tranche B are entirely paid off. The following figure shows the scheduled payments structure of a CMO.

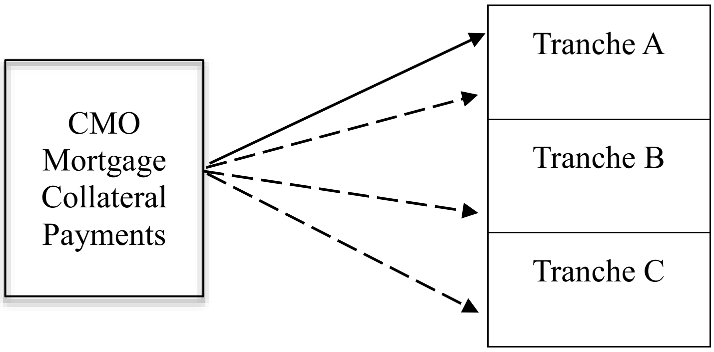

Figure 2.4: Cash-flow pattern for a CMO structure during the first five years

Source: Greenbaum and Thakor, 2011

Tranche A receives all principal payments and interest collected from underlying mortgage loans until it is paid off entirely within 5 years whereas tranche B and tranche C can only receive interest payments during 5 years. By scheduling cash flows this way, the CMO structure can reduce the variability of repayment rate and be used as a management tool of prepayment risk - which arises from borrowers prepaying their loans before maturity in order to refinance at lower rate when interest rates generally have fallen, especially for long-term mortgage without prepayment penalties. Therefore, financial institutions tend to invest in the lower level tranches in the CMO structure (the tranche C in the figure 2.4) in to reduce exposure to prepayment risk. Moreover, the CMO structure also can be used to manage banks' assets/liabilities. As an example, a Saving & Loan Association (S&L) has a 30 years fixed-rate mortgage financed with liabilities, so it is suggested that an S&L can swap its mortgage for top CMOs tranches with shorter maturities, avoiding problems with mismatching of maturities (Greenbaum and Thakor, 2011).

2.3 Mortgage Securitization

As mentioned, banks can sell off mortgage loans from their balance sheets after origination. There are two ways for banks to sell mortgage loans. One way is to sell loans to investors, such as hedge funds and mutual funds, in the secondary loan market where lenders buy and sell loans with investors and other lenders, allowing banks access to liquidity to generate more loans. In this case, banks only sell loans but do not securitize them. The other way is that loans can be offloaded to SPVs. Mortgage loans are purchased from banks and other lenders and are bundled into diversified portfolios in order to be sold into the securitization pool.

There is some risk in the process of loan sale since banks cannot sell originated loans immediately and need two to three quarters to sell those loans into the secondary market after the origination (Gordon and

D'Silva 2008). Banks hold mortgage loans in a sale pipeline, so a change in mortgage and securitization markets conditions may affect their performance and the selling process. Capital gains and losses will be generated on the mortgages held on balance sheet and in the sale pipeline if mortgage rates change. Moreover, if securitization markets collapse (private securitization market shut down in the financial crisis), banks are unable to sell loans and are forced to hold these loans in the pipeline.

Generally, a mortgage loan originated by banks can enter into the pool by several possible paths (see Figure 2.5). The most direct is that banks originate mortgage loans and put these loans into a securitization pool (see the first path in Figure 2.5), however, only a few large banks are able to originate enough mortgages to securitize them. The most common path from origination to securitization is that banks sell mortgage loans to either Government-Sponsored Entities (GSEs) or private firms (see the second path in Figure 2.5). Therefore, bonds backed by mortgage loans, typically Mortgage-backed securities (MBS), are issued by either GSEs (the GSEs that issue MBS are Fannie Mae and Freddie Mac) or private financial entities such as commercial and investment banks (MBSs issued by private firms refer to private-label MBS). Furthermore, it is possible that a mortgage is sold several times to other financial firms before it is placed in the GSEs or private firms MBS pools (see alternative path with dashed line in Figure 2.5). At the end of 2000, mortgage loan securitized by GSEs were more than $1.2 trillion, approximately four times the private securitization market (Passmore et al., 2002).

There are three main differences between loan sale and loan securitization. First, a loan sale merely transfers part of ownership of the loan portfolio from the originators to third parties, whereas securitization changes the pattern of cash flows. Second, claims against mortgage loans are sold as securities to investors in the capital market so that securitization has converted mortgage loans into marketable securities whereas assets in a loan sale are transferred from one bank to another without material qualitative asset transformation. Third, loan originators usually sell loans without explicit resources. Moreover, there are rarely guarantees, insurance, or other types of credit enhancement in the process of loan sale, but the originator is more likely to retain some portion of loans as a credit enhancement to reduce moral hazard. Loan sales offload the loans permanently from banks' balance sheets. Since our research focuses on OTD lending of mortgage loans, we introduce these two different types of mortgage securitization in this section.

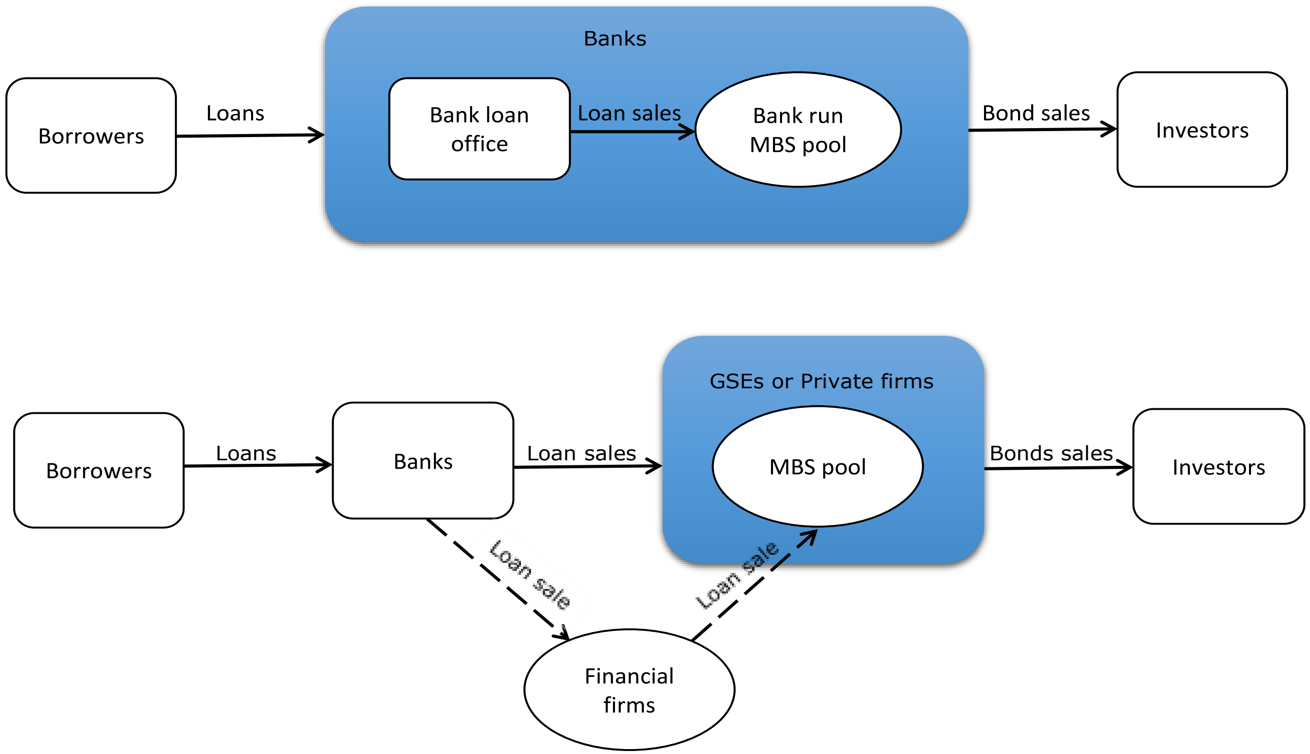

Figure 2.5: Several paths from origination to securitization Source: Rosen (2010)

2.3.1 Mortgage Securitization by GSEs

In the United States, the two biggest GSEs, The Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac) are insured by U.S. government guarantees. Fannie Mae was chartered by Congress in 1938 to support the secondary market for Federal Housing Administration (FHA) loans after The Great Depression and then was split into the current Fannie Mae and the Government National Mortgage Association (Ginnie Mae) based on the Housing and Urban Development Act of 1968. Freddie Mac was chartered as GSE in 1970. The main mission of Fannie Mac and Freddie Mac is to build a strong secondary market for mortgage loans. They made dramatic contributions to a sharp rise in the mortgage expansion and increased liquidity in the secondary market as they purchased almost half single-family mortgage loans and enable loan originators to generate more mortgage loans (Fabozzi and Modigliani, 1992).

Ginnie Mae plays a similar role to Fannie Mae and Freddie Mac. Unlike Fannie Mae and Freddie Mac, it can only purchase FHA, Veterans Administration (VA) and Farmers Home Administration (FmHA) insured mortgages. Since it is a direct agency of the federal government, principal and interest paid on time are guaranteed by federal government and investors are free of default risk of the pass-through issued by Ginnie Mae. Principal repayments and interest are guaranteed by Freddie Mac; however, payments of principal paid on time are not guaranteed as it is an indirect agency of federal government (Greenbaum and Thakor, 2011).

The GSEs tend to purchase mortgage loans from originators with high underwriting standards, so some stringent restrictions are imposed on mortgage loans bought by GSEs. Those mortgage loans that meet GSE restrictions are regarded as conforming loans. For example, loans sold to GSEs are typically first liens and the size of mortgage loans cannot exceed a conforming limit.[6] The conforming loan limit for a mortgage backed by a single-family residence was $41700 (Ashcraft and Schuermann, 2008). Moreover, loan-to-value (LTV) ratio of mortgage loans is usually below 80% and mortgage insurance is required if LTV ratio is above 80% (Passmore et al., 2002). In order to be able to sell loans to GSEs, the loan quality needs to meet GSEs standards and loans which are eligible for these standards are known as conforming loans.

[6]First lien mortgage is a mortgage in first lien position on the property that secures the mortgage. It has priority of repayment above all other liens in case of default. If the LTV ratio of first mortgage is above 80%, a private mortgage insurance (PMI) is required by lenders, so borrowers sometimes limit the size of first mortgage to an 80% LTV ratio rather than buying a PMI and borrowing the remaining amount by using secondary financing.

In addition, each GSE has its own way to select qualified mortgage loans. For example, if lenders want to sell mortgage loans to Fannie Mae, they first need to enter the loan and borrower data into Fannie Mae's designated underwriting software program, the DeskTop Underwriter. If some mortgage loans can satisfy Fannie Mae's criteria, these loans can be approved and sold to GSEs. If some loans fail to meet GSEs criteria but still fit private conduits standards, lenders will obtain approval and sell some of these loans to private conduits instead. Freddie Mac has similar software called Loan Prospector (Agarwal et al., 2012).

In most cases, the procedure for GSEs mortgage securitization is that conforming mortgages are bundled into pools by originators in order to sell to GSEs. Mortgage loans are purchased by agencies though either cash or swap programs (Fabozzi and Dunlevy, 2001). In the swap program, a lender obtains mortgage-backed securities in return by swapping large pools of mortgage loans against these securities. The GSEs buy small pools of mortgage loans from lenders and repackage them into large multi-lender pools, then issue securities backed by these pools and sell them to investors though the cash program.

In the securitization process, originators usually receive servicing fees for serving mortgage loans by collecting monthly repayments from borrowers. In each case, servicing fees collected by originators deducting costs can be realized profits for current period and originators can continue to earn fees for loan servicing without any credit risk. Since lenders transfer credit risk to GSEs, a guarantee fee and monthly cash flows from borrowers' repayments are paid to GSEs in return by taking the risk.

GSEs have some advantages in mortgage issuance over private firms since they are chartered by Congress. The most notable advantage is that GSE securities are backed by implicit government guarantees, allowing GSEs to issue debt securities at a lower interest rates relative to those issued by private firms. The Congressional Budget Office (1996) showed that the interest rate of MBS backed by GSEs was 40 basis points lower than that of MBS issued by a private firm. The benefit of this implicit subsidy can be passed on to prime mortgage market. Many previous studies provide evidence that the implicit subsidy allows mortgage rates for mortgage loans sold to GSEs to be lower than mortgage rates for non-conforming loans (Hendershott and Shilling, 1989). Second, their securities are treated as government securities in the Securities Exchange Act of 1934, which enables many trusts and other non-profit organizations to buy them. Third, due to implicit government backing securities, GSEs can securitize mortgage loans and then sell securities without holding capital or purchasing credit enhancements as required in private securitization. In addition, risk-based capital requirements for holding GSE-insured MBS are substantially lower than for holding private label MBS.

2.3.2 Mortgage Securitization by Private Firms

A market in non-agency mortgage-backed securities has developed since 1986. Some private institutions, Real Estate Mortgage Investment Conduits (REMICs) and the Real Estate Investment Trusts (REITs), can securitize mortgages which are known as "private-label" mortgage backed securities. Private firms appear to bear high credit risk and mainly purchase large numbers of mortgages with high loan-to-value ratios, those with relatively inadequate documentation and those with lower credit scores, which are referred to non-conforming loans. Non-conforming loans are either too large to meet conforming size limits (jumbos) or do not meet agency underwriting guidelines (Alt-A or subprime). Jumbo loans are defined such that the size of mortgage loans exceeds the maximum value set by GSEs. The Alt-A assets class typically includes loans made to borrower with good creditworthiness but do not meet underwriting criteria of GSEs. Subprime mortgages are loans made by borrowers who have lower credit scores relative to prime borrowers. These loans are mainly securitized by private issuers, such as investment banks and commercial banks.

Due to lack of implicit government guarantee provided by GSEs, private issuers have to protect securities holders from loss on the underlying mortgage loans. Many forms of credit enhancements are used to reduce credit risk of investors: subordination, over-collateralization, excess spread and shifting interests (Ashcraft and Schuermann, 2008). The most common way is a subordination structure. Pooled mortgage loans are split into multi-class securities. Different tranches of securities against mortgage loans are designed and sold to investors. The most junior tranche called "equity tranche" is the last to be paid and the first of all the tranches to suffer loss if mortgages loans in the pool fail to pay. The remaining junior tranches absorb further losses when the most junior tranche is exhausted. The equity tranche is generally created through over-collateralization. The principal balance of mortgage loans must exceed the value of all the debts issued by the SPV. Thus, the premium can absorb losses on the pool of mortgage loans.

The mezzanine class is used to absorb credit losses after excess collateral is reduced to zero. This class includes several tranches with ratings varying from AA to B. Since mezzanine investors bear relatively high risk, they receive the highest interest on their notes in return. The subordination is sum of over-collateralization and the width of most junior tranches. The top tranche, known as the "super senior tranche", has the lowest default risk and receives the highest rating from well-known agencies (such as Standard & Poor's or Moody's). Since the senior tranches are protected by over-collateralization and the width of the mezzanine tranches, they are the last to absorb the losses on the pool of mortgage loans and would pay the lowest interest rates to debt holders. Issuers sometimes retain some subordinated tranches of securities which bear most risk, so credit risk may not be completely transferred. In many cases, banks sell more senior tranches to investors and retain lower tranches.

Over-collateralization is another way to reduce credit risk. The rule is that the actual value of mortgages loans has to exceed face value of security against underlying assets. As we mentioned before, it is typically combined with a subordination structure. Excess spread also can reduce credit risks besides subordination and over-collateralization. The average weighted coupon from mortgage loans needs to exceed servicing fee to servicer, payments to the swap counterparty and the average weighted coupon on debts issued by the trust. The difference between average weighted coupon from underlying assets and payments needed to be paid to participants and investors in the process of securitization is defined as excess spread. It is in the first line to absorb loan losses. The principals of tranches are not be used to cover credit losses until excess spread becomes negative.

Shifting interest protects senior investors as all principle payments of senior tranches is required to be paid off in the first 36 months (the lockout period) before mezzanine classes are paid. During this period, holders of mezzanine tranches can only receive interest payments. The total share of senior tranches to entire deal decreases as principle payments are paid to holders of senior bonders; thus the amount of subordination of senior tranches increases. Finally, credit enhancements can be purchased from third parties, such as banks, insurance companies or GSEs. Those forms of credit enhancements can be letters of credit, surety bonds and other instruments. (Casu et al. 2013).

2.4 Mortgage Securitization in Prime Market and Subprime Market

Most loans underlying mortgage backed securities are made to prime borrowers (with good credit history) complying with underwriting standards of GSE. In addition to prime mortgages loans, nonprime mortgage loans are typically second liens or home equity line of credit (HELOC)[7] such as jumbo, Alt-A or subprime mortgage loans. These

[7] Second liens are more risky for lenders and usually have a relative higher interest rate compared to first liens because first liens are paid first. In the terms of foreclosure, holders of second liens can start the foreclose process when borrowers stop making payments but they only can collect repayments after first liens have been paid off. Home equity line of credit (HELOC) may require borrowers to pay a monthly payment requirement (at least greater than the

loans are mainly securitized by private firms. Due to the incentives of various participants, both origination and post-origination practices in securitization are different in the prime market and subprime market. The two figures from Agarwal et al. (2012) shown in the appendix demonstrate the main differences in securitization between these two markets (see appendix 2.1 and appendix 2.2).

On the origination side, the key difference between securitization in prime and sub-prime markets is underwriting criteria. Prime mortgage borrowers usually have higher credit scores, lower debt-to-income (DTI) ratios and better credit history than subprime mortgage borrowers. Due to the higher risk of subprime loans, subprime lending is mainly based on asset value rather than lenders' characteristics (Cutts and Van Order, 2005).

Second, since GSEs have a relatively high underwriting criteria, they usually buy 15-years or 30 years fixed-rate mortgages (FRMs) and only start to buy some hybrid adjustable-rate mortgages (ARMs) and interest-only mortgages at the peak of the cycle. In contrast, private label issuers can buy ARMs and other mortgage loans with higher spread which GSEs

minimum payment but less than the total outstanding). The full principal amount is due at the end of the draw period.

are not allowed to purchase, which means private label issuers may have higher preference for default risk.

Third, the difference in the origination practice is reflected by the fact that subprime originators are largely dominated by some specialized subprime lenders. Department of Housing and Urban Development (HUD) uses Home Mortgage Disclosure Act (HMDA) data and conducts interviews with lenders to identify subprime lenders. A list of 210 subprime lenders was published by HUD in 2005. It shows subprime specialists having fewer originations and a higher share of refinance loans from total originations. Moreover, they also sold a smaller percentage of their portfolios to GSEs. One important thing which is pointed out in the report is that some prime lenders originate large amount of subprime loans and some subprime lenders also originate prime loans.

Fourth, GSEs offer guarantees against default risk to investors, so default risk is retained in GSEs rather than being passed to investors. However, subprime lenders usually sell mortgage loans to non-GSE private conduits. Cash flows against mortgage loans are not guaranteed and private label issuers tend to pass default risk to investors who want to bear it. Additional credit enhancements against credit risk are provided by a third party but these credit enhancements typically cover losses only up to a certain amount.

Last but not least, securities sold to investors differ in prime and subprime markets. In the prime market, securities typically have a simple pass-through structure, so investors have the same contacts and receive the same amount of monthly principal and interest. In contrast, an MBS usually has a complicated and subordinated payment structure in the subprime market.

2.5 The Trend of Securitization

The securitization market developed in the United States since 1970. In 1971, the first pass-through security was issued by Ginnie Mae. The federal government allowed Fannie Mae to buy private mortgages which were not originated by the agency.[8] Meanwhile, a secondary market for conventional mortgages established since Freddie Mac was chartered to provide stability and liquidity during the severe credit crunch of 1969-1970 in the thrift industry.[9] Freddie Mac created a similar pass-through

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[8]There are three main types of mortgage loans for people to finance their home, VA, FHA as well as conventional mortgage loans. In general, Fannie Mae purchase mortgages insured by FHA and Freddie Mac mainly buy FHA and VA mortgages loans.

[9] Conventional mortgage loans are typically made by private entities such as banks, credit unions, private lenders or thrifts. Unlike VA and FHA mortgage loans (non-conventional mortgage loans), Conventional mortgages are not guaranteed by federal government, but they have to comply with mortgage guidelines set by Freddie Mac and Fannie Mac. Conventional loans can be

called “participation certificate” (PC) in 1971. Fannie Mae created its first pass-through MBS in 1981. Since Fannie Mae and Freddie Mac have been able to purchase mortgage loans from all types of lender since the 1990s, they have played a very important role in a rapid growth of mortgage securitization.

Figure 2.6 presents the amount of outstanding and securitized home mortgage loans over the period 2000 to 2014. It shows that the total amount of outstanding home mortgage experienced a steady increase from $ 5.1 trillion to $14 trillion in 2009. The total volume of securitized home mortgage loans has developed since 2000 from $2.8 trillion to $ 6.8 trillion in 2009, thus almost half home mortgage loans have been securitized. However, it suffered a substantial decline to approximately $2.2 trillion in 2014.

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conforming and nonconforming. Loans above the limits of Freddie Mac and Fannie Mae are called nonconforming loans or jumbo loans.

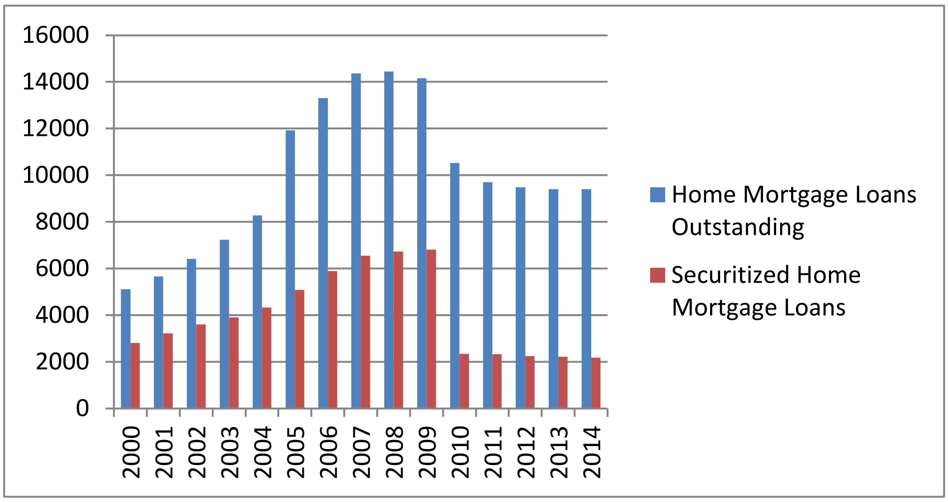

Figure 2.6: Outstanding and securitized home mortgage loans

Figure 2.6 shows outstanding and securitized home mortgage loans from 2000 to 2014, reported in billions of dollars. We collected these data from US flow of funds account. Home mortgages outstanding are taken from Table L.2 item FL193165105. Home mortgages securitized are computed as the sum of item FL413065105 from Table L.125 and item FL673065105 from Table L.126.

Securitization was limited to home mortgages and other types of loans could not be securitized in 1976. Securitization of other variable classes of assets, like commercial mortgage loans, C&I and consumer credit has begun since the 1990s. By the end of 2007, the total amount of securitized commercial mortgages, C&I loans and consumer credit would be $652 billion, $80 billion, $682 billion respectively (Loutskina, 2011).

In 1977, the Bank of America issued the first private-label RMBS pass-though. The emergence of private issuers (non-agency) allowed banks to lower their lending standards and make more sub-prime loans which did not meet GSEs underwriting standards. The first subprime-backed RMBS deal was established in the early 1990s. Due to relative low interest rate and rising house prices, there was a rapid growth in subprime lending, accounting for more than 20 percent of total mortgages to 2006. The issuance of US private-label MBS exceeded GSEs issuance for the first time in 2005. Private-label RMBS issuance increased from $148 billion in 1999 to $1.2 trillion by 2006 and its share of total issuance increased from 18 percent to 56 percent (Segoviano Basurto et al., 2013). At the end of 2008, about $5 trillion out of $7.6 trillion total pooled mortgage were securitized by GSEs while private firms securitized the remaining $2.6 trillion (Agarwal et al., 2012).

The default rate of subprime adjustable-rate mortgages has risen since 2006, but some risk measures, such as corporate bond spread and the Chicago Board Options Exchange's Volatility index (VIX), are still at an historical low level (Rosen, 2010). Also, haircuts on the securitized products in the repo market have been very small (Gorton and Metrick, 2012).[10] The credit rating agencies started to downgrade rating of some risky MBS as housing price began to decrease since mid-2007. Some

[10] Haircuts measure the excess amount a firm must pay to use an asset to be collateral. A 10% haircut means that $100 dollar collateral needs to be offered for a $90 loan. The higher the haircut, the safer the loan is for a lender.

major problems of securitized products have emerged due to losses on mortgage-related products and several subprime mortgage lenders went into bankruptcy.

As private securitization markets dried up in mid-2007, many mortgage loans origination for resale (pipeline loans) became stuck on bank balance sheets when the private securitization markets shut down during 2007-2009 financial turmoil (Purnandam, 2011, Gordon and D'Silva, 2008). Regulators pump money into economy directly (Quantitative Easing) when interest rate cannot be lowered any more, preserving sufficient liquidity in credit risk transfer (CRT) markets. The Federal Reserve has bailout of Fannie Mae and Freddie Mac and can take certain types of Assets-Backed securities (ABS) as collateral in monetary policy operations (Adrian and Shin, 2010). Therefore, banks retained the ability to sell loans for securitization since MBS backed by Ginnie Mae, Fannie Mae and Freddie Mac could be created during the turmoil.

Chapter 3

Literature Review

3.1 Introduction

In the traditional banking business model, illiquid loans are information-sensitive and some informed traders can use private information to trade them, so they cannot be sold without frictions in the capital market. Indeed, Gorton and Pennacchi (1990) suggest that a security needs to be created for transactions to protect uninformed investors and Gorton (2009) notes an imperative for banks to create a new information-insensitive debt. Loan sale and securitization create this form of security, leading to a fundamental change in the bank business model from "Originate-to-Hold" to "Originate-to-Distribute" (OTD). Two important fundamental roles, liquidity transformation (Diamond and Dybvig, 1983) and delegated monitoring (Diamond, 1984), have been changed by the OTD model. Banks issue demand deposits and allows depositors to withdraw money when they need. As banks are able to offload loans from their balance sheets, additional source of funding can be raised through selling loans to finance loans and liquidity, making banks less dependent on traditional funding source (Diamond and Rajan, 2001; Loutskina and Strahan, 2009; Loutskina, 2011). In addition, banks are delegated to monitor borrowers' behavior, minimising incentives problems between borrowers and lenders, however, banks tend to reduce incentives to monitor borrowers after selling these loans (see e.g. Pennacchi, 1988; Gorton and Pennacchi, 1995; Keys et al., 2010; Purnanandam, 2011).

This chapter is organized as follows: In Section 3.2, we review the determinants of participation in the OTD model and which actual roles the OTD model has played. Section 3.3 provides a literature review of its impact on credit supply and bank performance. At last, section 3.4 concludes the chapter.

3.2 The Motivations of Using the OTD Model

The OTD model allows banks and other non-financial firms to sell illiquid assets rather than holding them until borrowers have repaid. Questions on the incentives driving banks to sell or securitize loans then arise. Previous literature suggest the main motivations of securitization are: (1) regulatory capital arbitrage, (2) risk sharing and transfer, and (3) liquidity and funding needs.

3.2.1 Regulatory Capital Arbitrage

Under the Basel I framework, regulators set capital requirements without considering banks' risk levels. It allows banks to hold sufficient capital to bear default losses. Specifically, if a bank wants to make loans to a firm, 8 percent of capital is required no matter what the risk level of the firm. Since 1999, Basel II has been in place, revising this capital regulatory framework and requiring banks to hold more capital for riskier loans. Thanks to loan sale and securitization, banks can sell a portion of their loan portfolios and with the proceeds lend to riskier borrowers, leading to an increase in expected return of their loan portfolios without the change in capital requirements. This process is referred to "regulatory capital arbitrage" (RCA). [11] The regulatory framework (Basel I and later Basel II) has contributed to an increase in securitisation (Pozsar et al., 2010; Gorton and Metrick, 2010) and securitization allows banks to alleviate regulatory capital requirements with little or no reduction overall economic risk (Avery and Berger, 1991; Jones, 2000).

The OTD model allows lenders to sell loans from their balance sheets to finance new loans at a lower cost than issuing traditional deposits, lowering cost of capital by saving reserves and capital requirements set up by regulators (Gorton and Pennacchi, 1995). This avoids the cost related to required reserves and capital charges related to loans on

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[11] In this case, banks usually have an incentive to sell or securitize higher quality assets since same capitals are charged to broad classes of assets by regulators.

balance sheets (Pennacchi, 1988). James (1988) suggests that bank regulation is not the only reason for loan sale. In particular, capital requirements accelerate underinvestment problems of banks and increase incentives to be involved in off-balance sheet activities because loan sales enable banks to finance loans less expensively, avoiding an underinvestment problem. The problem was posed by Myers (1977) and it arises from the fact that firms with risky debt outstanding tend to pass up on new investments with positive net present value. He indicates that loan sale can reduce potential wealth transfers from shareholders to depositors when banks ought to fund profitable investment opportunities. [12] Consistent with James (1988), Jones (2000) also suggests that regulatory capital arbitrage is not the only incentive for banks to securitize loans and banks tend to engage in the securitization because of increased economic of scale, reduction of cost of debt financing and funding source diversification.

Some empirical evidence has been provided to support the regulatory arbitrage hypothesis. Cebenoyan and Strahan (2004) find that banks can manage their credit risk through loan purchase and sales in the secondary market. They find that the risk-assets weight ratio of banks active in

[12] Lenders would sell a portion of cash flows related to new investments by providing investors with a senior claim to those cash flows, so lenders may fund those opportunities which result in potential wealth transfers.

buying and selling loans is 7% to 8% lower than for banks not involved in this market. Moreover, the capital ratio of the buy-and-sell banks is 1% to 1.3% lower than banks that only sell loans. Martin-Oliver and Saurina (2007) investigate the motivations of securitization by using different types of assets-backed securitization in Spain. They find evidence of arbitrage capital in the loans to small and medium size firms. In contrast, Bannier and Hänsel (2007) investigate the determinants of loans securitization by examining collateralized loan obligation (CLO) of European banks from 1997 to 2004. They find that banks with low tier 1 capital ratio have less incentive to securitize relative to high tier 1 capital ratio banks. This indicates that there is no evidence of regulatory capital arbitrage driving securitization under the Basel I framework.

Calem and LaCour-Little (2004) suggest that the current capital requirements are very high for loans with low risk and are relatively low for loans with high risk under Basel I, so banks prefer to securitize less risky loans and keep riskier loans in their portfolio. Ambrose et al. (2005) also provide evidence of regulatory capital arbitrage in mortgage securitization by comparing default rates between securitized and non-securitized loans by using single lender data and find that the default rate of securitized loans is much lower than loans which are not securitized. The results indicate that regulatory arbitrage prevents banks from using information advantage and tend towards retaining risker loans. However, it is argued that regulatory capital arbitrage cannot be used under the Basel II. Archaya et al. (2013) also suggest that regulatory arbitrage is an important motivation to engage in the securitization by using one form of securitization, asset-backed commercial paper (ABCP).

However, Calomiris and Mason (2004) explore whether banks are engaged in regulatory arbitrage by using the data of credit cards securitization. The findings support efficient contracting and suggest that securitization with implicit sources is beneficial to avoid the minimum capital requirements.

Minton et al. (2004) also support an efficient contracting hypothesis against regulatory capital arbitrage and suggest that less capitalized banks are less likely to be involved in the securitization process than banks with high capital ratios.[13] They also find that unregulated investment banks and financial companies tend to securitize more than banks. This also implies that securitization is not motivated by capital regulation.

13 The efficient contract hypothesis is that securitization with implicit recourse may be efficient, rather than an attempt to abuse government safety net protection by maintaining inadequate capital. We call this the "efficient contracting". Bank safety net includes a direct access to deposit insurance, the discount window and the payment system.

3.2.2 Risk Sharing and Transfer

There are two motivations for securitization which possibly lead to riskier loans being sold. The first is risk-sharing or diversification, particularly of interest-rate, credit, or house-price risk. Since loans can be sold from balance sheet, banks can transfer risk from the banking system to other sectors in order to improve risk sharing with the rest of the economy (Allen and Carletti, 2006). Moreover, securitization allows banks to pool high quality loans with relative low quality ones to gain a better credit rating. For example, securities with AAA rate may be contracted by combining AAA-rated and BBB-rated securities. Therefore, securitization spurs some agencies who cannot participate in the market to have access to mortgage structured products to share risk, such as money funds and pension funds which only can invest in the assets portfolio with AAA credit rating.

Another is related to risk transfer driven by the adverse selection (Akerlof, 1970). Since lenders have more private information about credit quality of borrowers, they have incentives to sell inferior loans and retain higher-quality loans on balance sheet by using information advantages (see for example, DeMarzo and Duffie, 1999, and Parlour and Plantin, 2008). In contrast with securitization motivated by risk-sharing, such loans will be riskier even after controlling observable information available to investors (Elul, 2011).

It is widely acknowledged that securitization is beneficial for banks to stabilize the banking system because they do not need to bear default risk by selling loans from balance sheet to other financial institutions, at least this appeared so before the financial crisis. Many studies provide evidence of risk transfer and suggest that riskier banks have more incentive to participate in the OTD model (Gorton and Souleles, 2006; Bannier and Hänsel, 2007; Affinito and Tagliaferri, 2010).

Gorton and Souleles (2006) present a model to test the reasons for the existence of SPVs (Special Purpose Vehicles) and suggest that the main motivation for using SPVs is that they reduce bankruptcy costs. They test empirically using data for credit card ABS. Since it is very difficult to measure bankruptcy cost, they use the riskiness of the firm measured by its bond rating as a proxy. The results indicate that riskier firms are more likely to be involved in the securitization process.

Bannier and Hänsel (2007) examine whether different firm-specific variables have an influence on the decision of securitization of European CLOs. Their results show that banks with low performance are more likely to securitize, which is evidence against "appetite for risk" hypotheses in order to increase bank performance. This indicates that securitization is used as a tool to transfer bank risk, but risk transfer appears limited since tranches with higher credit risk seem to be retained.

Drucker and Puri (2006) and Duffie (2008) argue that banks tend to retain lower quality loans and sell of high-quality loans on the condition that the return of lower-quality loans is higher than that of good quality loans and economic capital which ensures survival of banks in the worst case is much less than regulatory capital.[14] Affinito and Tagliaferri (2010) control for the effect of bank regulatory capital and return and suggest that the results remain supportive of risk transfer.

In contrast, the literature believes that banks will not sell off bad loans due to reputation concerns. Ambrose et al. (2005) investigate whether lenders tend to use information advantage about borrowers to sell riskier loans to the secondary market and retain less risky loans in the portfolio by using data of a single lender between 1995 and 1997. They compare conditional default rates of securitized loans and non-securitized loans and find that securitized loans have a lower ex-post default rate relative to loans held by banks, which indicates that mortgage loans with lower default risk are more likely to be securitized under either case. Their results can support either regulatory capital arbitrage or reputation

[14] Economic capital is determined internally based on economic conditions to ensure the survival of financial institutions in the event of the worst scenario whereas regulatory capital is set up externally by regulators.

explanation.[15] However, the data contain only one single lender and this does not mean that the conclusion will be true for all banks. Albertazzi et al. (2015) also examine the relationship between securitization and loan performance by using mortgages data originated by 50 Italian banks from 1995 to 2006. They suggest that securitized loans have lower default rate than non-securitized ones, which indicates that banks care about their reputation and more likely to sell good loans. Furthermore, many studies believe that bad loans are retained and securitization is not able to transfer risk to investors. As argued by Shin (2009), bad loans are retained in either the balance sheets of financial institutions or in SPVs sponsored by them, so financial institutions are still exposed to credit risk. In line with Shin (2009), Achaya et al. (2010) and Acharya and Schnabl (2013) use data from asset-backed commercial paper and provide evidence that securitization does not disperse credit risk as commercial banks suffer most losses rather than investors.

3.2.3 Funding and Liquidity Needs

The third reason is that banks use the OTD model to meet their own liquidity needs since they can raise funding from selling loans from their balance sheets rather than attracting deposits from savers. Diamond and

[15] Due to the repeated structure of securitization, banks have concerns about credit quality and tends to maintain their reputation in the market to make sure that they will not lose market access.

Rajan (2001) regard loans as relatively illiquid assets so that banks suffer liquidity risk by holding them. When market liquidity falls, they may securitize the loans to obtain liquidity. Since banks can liquidate loans though securitization, they would rely less on financing in traditional ways. DeMarzo and Duffie (1999) and DeMarzo (2005) develop a theoretical model for security design and find that one important motivation for securitization by banks is to finance liquidity on the balance sheet. Martin-Oliver and Saurina (2007) examine the determinants of securitization in Spain and suggest that the main motivation for banks to securitize is to meet liquidity needs. Farruggio and Uhde (2015) also investigate why banks securitize loans among European banks by using 75 securitized banks and non-securitized banks in the EU-13 plus Switzerland from 1997 to 2010. The results indicate that liquidity needs drive loan securitization, especially during a crisis period.

Moreover, the OTD model provides an additional source of funding, allowing banks to hold less liquid assets on their balance sheets (Cebenoyan and Strahan, 2004; Affinino and Tagliaferri, 2010, Loutskina, 2011). Cebenoyan and Strahan (2004) find that banks that manage their risk by buying or selling loans seem to have lower liquid ratio than other banks. Research indicates that banks will decrease their holdings of liquid assets since they have an increasing ability to liquidate loans (Loutskina, 2011).

Besides the above, there are some other incentives of using the OTD model mentioned in the literature. Purnanandam (2011) suggests that banks with more OTD mortgage loans tend to sell these loans, so mortgage OTD lending is included to measure the OTD level that banks achieve. Bendendo and Bruno (2012) argue that banks with less non-interest income would like to engage in the OTD model as banks could generate fees through OTD activities. Besides banks' characteristics, Bannier and Hänsel (2007) suggest that some macroeconomic factors drive banks to securitize loans, securitization is positively affected by both GDP growth and interest rate.

3.3 The OTD model, Credit Supply and bank performance

The OTD model allows banks to obtain liquidity from selling loans, increasing the willingness for making more loans to the economy. There are many studies about the relationship between OTD activities and credit supply. Cebenoyan and Strahan (2004) suggest that loan sales lead to an increase in credit supply, leading to an increase in bank leverage and profitability. Dell' Ariccia and Marquez (2006), Demyanyk and Hemert (2011) and Dell' Ariccia et al. (2012) document an increase in the credit supply driven by lowering lending standards. Mian and Sufi

(2008) and Loutskina and Stranhan (2009) also find evidence of a credit expansion by using loan-level data. As for European banks, Altunbas et al. (2009) also arrive at similar conclusions that banks that are active in the securitisation market also seem to supply more loans for the period between 1999 and 2005. Goderis et al. (2007) confirm these findings with an international dataset using data from 65 securitisation active banks between 1995 and 2004.

The OTD model has been considered to have beneficial effects on banks in terms of credit supply to the economy. However, it is widely known that securitization played a very important role in this financial crisis and contributed to the delinquencies of large amount of mortgage loans. Many empirical researches show that securitization led to the poor performance of mortgages originated before crisis. Many possible explanations are provided in the literature.

First, the excessive expansion of credit supply through securitization could be one reason for higher default rates of mortgage loans in the recent financial crisis. Mian and Sufi (2009) examine the impact of securitization on default rate by using zip-code level information. They find that zip codes with high latent demand have an excessive credit supply, leading to a higher default rate in those regions from 2005 to 2007. Extending earlier work, Demyanyk and Hemert (2011) investigate credit expansion from the demand side and use higher volume and lower interest rate to proxy an increased demand for subprime MBSs. Increased origination of mortgage loans leads to a deterioration of loan quality, leading to a higher delinquency rate. Specifically, loan originations in 2006 and 2007 show a much poorer performance relative to previous loans origination from 2001 to 2005. The results suggested that all kind of mortgage loans suffered a higher default rate, not only limited to hybrid or low-documentation mortgages.

Loutskina and Strahan (2009) maintain that banks with more liquid assets and lower deposit costs will generate more illiquid jumbo loans which tend to lower the quality of portfolios. Consistent with the evidence provided by Demyanyk and Hemert (2009), Dell'Ariccia et al. (2010) also examine the relationship between credit expansion and default rate in the subprime mortgage market. They find that the relationship is associated with decreased lending standards, measured by a decline in loan denial rates and an increase in loan-to-income ratio. The evidence indicates that a decrease in lending standards which resulted from the competition among banks lead to an increase in mortgage supply. High default rate is attributed not only to an excessive credit supply, but also to a decrease in lending standards which is another apparent reason for the crisis. As banks have private information about borrowers and information asymmetries decrease, they seem to ease lending standards. Dell'Ariccia and Marquez (2006) suggest that decreased lending standards lead to an increase in lending volume and a deterioration of loan portfolios.

Second, one possible reason for poor bank performance is related to adverse selection (Akerlof, 1970). Since lenders have more private information on credit quality of borrowers, they have incentives to sell inferior loans and retain higher-quality loans on balance sheet by using information advantages. However, it is also possible that securitization can reduce the risk related to asymmetric information. As mentioned earlier, Ambrose et al. (2005) investigate whether lenders tend to use this information advantage about borrowers to sell riskier loans to the secondary market and retain less risky loans in the portfolio by using data of a single lender between 1995 and 1997. They first estimate a model based on the prepayment and default status of the mortgages originated in 1995 and 1996 to predict the prepayment and default probabilities for mortgage originated in 1997. In the second step, they use these estimated probabilities as an explanatory factor to examine the probability that a mortgage loan originated in 1997 is either securitized or retained in the portfolio. They compare conditional default rate of securitized loans and non-securitized loans and find that securitized loans have a lower ex-post default rate relative to loans held by banks, which indicates that mortgage loans with lower default risk are more likely to be securitized under either case.

Elul (2011) examines the effect of securitization on loan performance by using a loan-level data set from LPS Analytics and focus on mortgages originated in 2005 and 2006 including both securitized and non-securitized loans. He finds that private-securitized loans have a 20 percent higher default rate than portfolio loans in the US prime mortgage market, which is consistent with the adverse selection hypothesis between lenders and investors. By contract, the default rate of securitized loans tends to be much lower than bank-held loans in the subprime market. This can be fully explained by “early defaulting” loans. Specifically, mortgage loans intended to be sold usually would stay in the “pipeline” for several months. However, lenders may intend to sell risky loans and cannot sell them now if these loans have suffered default before selling to the securitization pool. As he excludes all delinquency loans within six months after origination, he observes the sign of securitization coefficient is reversed for both subprime loans and adjusted-rate subprime mortgages, resulting in that private-securitized loans are riskier than loans which are not securitized by private issuers in the subprime securitization. He also examines the effect of securitization on loan quality across different documentation types of mortgages. In the prime market, although private-securitized loans are much riskier for all documentation types, this effect is a bit stronger for low and no documentation loans. Moreover, he finds that the effect of private securitization is more pronounced for subprime loans with low and no documentation. There is no evidence that securitized loans are riskier for subprime FRM and full documentation loans. Therefore, the effect of securitization is concentrated in low or no documentations loans, which is in consistent with Keys et al. (2009).

Agarwal et al. (2012) examine whether loan quality of mortgage loans retained on the balance sheet by lenders differs from that of mortgage loans sold to secondary market by using loan-level data between 2004 and 2007. They compare the quality of two groups of loans across two different securitization market segments, prime mortgage market and subprime mortgage market. Despite using different data source from Ambrose et al. (2005), they still obtain similar results that securitized loans have a relative lower default rate compared to loans retained on the balance sheet for each year from 2004 to 2006. Results indicate that most banks are more likely to sell loans with low default risk to GSEs and retain loans with high default risk in their portfolio. However, banks are not willing to retain high default risk loans and they find evidence that banks tend to securitize loans with high default risk after the financial crisis as the private label securitization market has crashed due to the downturn of house price and tighten credit supply. They also investigate adverse selection in the mortgage securitization with respect to two types of risk, prepayment risk and default risk, which lenders mainly face with. In terms of prepayment risk, they provide evidence that securitized loans have a relative higher prepayment risk compared to bank-held loans in the prime market to support adverse selection. In contract to the prime market, there is no such a clear pattern of adverse selection in the subprime market.

Third, banks have information advantages about borrowers when they are carrying out lending business, whereas loan buyers do not have proprietary information about borrowers and are more likely to be in a disadvantageous position when buying loans from originated banks. As a result, a moral hazard problem exists in the loan sales (Pennacchi, 1988). Since securitization allows banks to offload illiquid loans from balance sheet, they only need to bear the pipeline risk of holding loans until sold (Rosen, 2010) and would be unlikely to expend sources to manage the credit risk by monitoring and screening borrowers' behaviour.

Parlour and Plantin (2008) build a theoretical model to show that the secondary market provides an alternative way to fund illiquid loans. Banks can sell non-performing loans in the liquid mortgage market, allowing them to have additional funds to invest into other opportunities, but reducing the banks' incentives for monitoring borrowers.

Stein (2002) distinguishes between soft and hard information and claims that it is likely that soft information is not easily communicated and verified in an unambiguous way. Banks decide whether or not to make loans primarily based on hard information which can be documented in a report, such as a FICO Score. Besides that, they need to expend effort to collect soft information to monitor borrowers' behaviour. However, it appears that less private information is collected because securitization allows banks to transfer illiquid assets and credit risk to the ultimate holder of loans (Rajan, Seru and Vig, 2009).

Mian and Sufi (2008) demonstrate a positive relationship between the growth in defaults and the growth in mortgage sales which provides evidence that moral hazard problems lead to the mortgage expansion though securitization. Keys, Mukherjee, Seru, and Vig (2009; in the following referred to as 'KMSV') find empirical evidence that the ease of securitization contributed to a weak incentive to screen borrowers. They assume that mortgage loans around the threshold for granting individuals loans have similar loan characteristics and compare delinquency rate above and below the cutoff. The results indicate that loans with higher likelihood to be securitized have a higher default rate than those with relative low probabilities to be securitized. It seems reasonable to suppose that banks lacked incentive to monitor sold loans.

Bubb and Kaufman (BK, 2009) exploit an exogenous cut-off rule to examine the KMSV explanation. Based on the KMSV study, they suggest that loans made by borrowers' FICO Scores above 620 are easily sold to originators. Banks have less incentive to monitor them and will only expend resource to risky loans (below 620 in this case), so securitized loans have higher (than otherwise expected) default rates for loans above the cutoff. They shows that loan default rate of borrowers' FICO Score above 620 is higher than those below, apparently supporting the KMSV explanation that banks with monitoring difference around the cut-off contributed to discontinuity of default rate. However, there is no difference in securitization rate in their empirical results and so KMSV might not be true. A reasonable explanation for this phenomenon is given by Keys et al. (2010) after they replicated work of BK. An explanation for BK's findings is that they pool various types of loans into their samples, including loans sold to GSEs and full documentation loans, rather than focusing on the non-agency subprime mortgage loans. Therefore, loans sold to GSEs and full documentation loans have no difference in both the default rate and securitization rate around the FICO Score cutoff. In this paper, they provide evidence that securitization decreases lending standards of banks around the FICO

Score of 620 in the subprime mortgage market. More loans have been securitized above the cutoff. They confirm their previous results that there is a discontinuity in both securitization and default rate around the cut-off in the low documentation subprime mortgage loans, indicating that securitization reduce incentives of monitoring. However, the validity of this argument is based on an assumption that the discontinuity in screening borrowers at credit score cutoff is exclusively driven by a jump in the probability of securitization at the cutoff. Bubb and Kaufman (2014) suggest that this crucial assumption does not hold, so the discontinuity in default rate at the cutoff cannot provide evidence that securitization lacks the incentives of monitoring and screening.

Brunnermeier (2009) investigates the reasons for the financial crisis in 2007-2008 and concludes that banks with high involvement in the OTD lending model partially contributed to this crisis. As banks offload risk to third parties, they have less incentive to monitor and screen borrowers, contributing to an increase in mortgage default rate. Purnanandam (2011) provide empirical evidence that banks with high OTD loans originated in the pre-crisis period dilute monitoring incentives and trigger higher default rates and charge-offs when the financial crisis occurs. Large numbers of poor quality loans are retained in the balance sheet of banks and cannot be sold out since the securitization market has dried up, so these loans contribute more to default rate.

However, Froot & Stein (1998) and Cebenoyan & Strahan (2004) suggest that banks can manage their credit risk by loan purchase and sales. At the same time, this encourages banks to take more risk. They find that banks that buy and sell loans are more likely to hold risker loans (C&I loans and real estate loans). Moreover, Jiangli and Pritsker (2008) examine the impact of mortgage securitization on insolvency risk by using US BHC data from 2001 to 2007 and suggest a negative relationship between securitization and the insolvency risk. Casu et al. (2011) also use the BHC data and find this significant negative relationship mainly associated with securitization of mortgages and home equity lines of credit.

Jiang et al. (2014) examine the ex-ante and ex-post relationship between securitization and bank performance by using major lender data between January 2004 and February 2008. For ex-ante relationship, the higher the probability is that loans can be sold, the higher is the default rate loans tend to have. However, their results indicate that sold loans have lower default rate than retrained loans on balance sheet after loan sale, which is consistent with Ambrose et al. (2005).[16]

16 The ex-ante relationship is that between the probability of loans that became default and the probability of loan sale given the information available at the time of loan origination. The ex post relationship that between the probability of loan default and loans actual sold based on the information known at the time of loan sale.

3.4 Conclusion

This chapter gives an overview of literature associated with the OTD model. We first review the motivations for using OTD model. Based on the literature, it is argued that there are three main incentives for banks to engage in the OTD model: regulatory capital arbitrage, risk transfer, funding and liquidity needs. We find a gap in the literature which motivates us to investigate the motivations of OTD model of lending based on involvement in the OTD model and bank size. Then, we present a summary of literature on the impact on credit supply and bank performance. In general, the OTD model increases the supply of credit, leading to poorer bank performance. Moreover, poor bank performance could be driven by agency problems. Finally, we see that the literature offers ambiguous views on the relationship between the OTD model and bank performance and suggests that more research need to be done in the future.

Chapter 4

Data Collection and Research Methodology

4.1 Introduction

This study aims to investigate what determines US banks' choice of the OTD model of lending and the impact of the model on bank credit supply and risk-taking behavior. In particular, the study is based on three questions: 1) Why do banks engage in the OTD model of lending? 2) Does the OTD model increase the credit supply of US banks? 3) How does the OTD model affect bank risk taking behavior? To address these research questions, it is important to choose an appropriate research methodology, collecting and analyzing appropriate data. This chapter describes the research methods used in the study. The chapter is organized as follows. Section 4.2 presents details on the data collection process. Section 4.3 provides an overview of research methods used to conduct the research. Section 4.4 sums up the chapter.

4.2 Data collection

In order to achieve the aims of the study, data on US banks' financial statements and US macro-economic variables need to be collected. The following sections give details of data sources and procedures for dealing with those data.

4.2.1 Sources of data

Financial and accounting data of US banks are collected from the Consolidated Report of Condition and Income (Call Report) which must be completed by all commercial banks in the US. Call Report data provide detailed information about the on-balance sheet and off-balance sheet activities of banks. As mortgage loans sale and securitization activities increased dramatically in the recent years, banks started to report their 1–4 family residential mortgage origination activities in the Schedule RC-P of Call Reports at the beginning of the third quarter of 2006. The Schedule is filed by banks with more than \$ 1 billion total assets and by small banks with more than \$10 million of mortgage business. Information about financial statements of US banks is also collected from Call reports from 2006Q3 to 2009Q2. Finally, macro data, the real GDP and House Price Index (HPI), are collected from the U.S. Bureau of Economic Analysis and the Federal Housing Finance Agency, respectively.

4.2.2 Sample selection

The sample period runs from the third quarter of 2006 to the second quarter of 2009. There are two main reasons for conducting our study during this period. One reason is that the data of OTD model of lending activities are only available from the third quarter of 2006. The other is that the private securitization market was shut down during the financial crisis, leading to a decrease in the OTD model of lending activities, so we do not consider the mortgage origination for resale after 2010. After collecting the original sample from Call Reports, we pose the following restrictions to selection of our research sample. First, we require bank data to be available in each quarter. Second, banks with zero value for total assets, total 1–4 mortgage loans, total deposits and total capital are excluded from the sample. Since we want to investigate variation of the OTD activities of the same bank over time, we have to make sure that mortgage origination and mortgage sold data are available. Thus, we remove missing or zero values for mortgage origination and sale since they are not involved in the OTD model by definition. Finally, only mortgage origination and sold data available for at least three consecutive quarters are selected in the whole sample. To eliminate outliers, all bank variables are winsorized at the 1% and 99% level.

In our study, we also divide the whole sample into sub-samples based on the objectives of our research:

1) Following Purnanandum (2011), we divide our sample into low-OTD and high-OTD banks based on the average value of origination for resale across all quarters because we would like to examine whether low- and high-OTD have different incentives to use OTD model of lending and the its impact on credit supply and bank risk-taking.
2) We divide our sample into small banks and large banks in two different ways. We use a method similar to that of Cornett at al. (2011) to define small and large banks. Small banks are those with total assets at the beginning of a quarter less than 1 billion dollar and large banks are those banks with total assets with more than 1 billion dollars. We want to investigate the motivations for using the OTD model of lending and whether it leads to an increase in loan supply and bank risk vary across bank size.

4.3 Data Analysis

In the literature, the most commonly used methods for panel data in this area are Fixed Effect Model (FE) and Generalized Method of Moments (GMM). To ensure the reliability of our empirical results, we consider both methods. The following two sections discuss and justify OLS with fixed effects estimator and system GMM as the most appropriate method for our study.

4.3.1 Fixed Effect Model

A panel dataset is one in which each variable contain information on N units and each unit contains T time-series observations. Panel data regression differs from a regular time series or cross-section because it combines both in a double subscript on its variables. The equation can be written as follows:

$$y_{it} = \alpha + \beta x_{it} + \mu_{it} \qquad (4.1)$$

$$\mu_{it} = u_i + \varepsilon_{it} \qquad (4.3)$$

where i and t represent individual banks and time periods respectively. y_{it} is dependent variable and x_{it} is an explanatory variable. α is the constant and β is the slope of the explanatory variable which reflects a partial explanation or prediction for the value of Y. u_i is unobserved individual specific effects and ε_{it} is a white noise error term.

The simplest way to analyse such data is to estimate a pooled regression, which means that the single equation is estimated based on all the data together. However, there may be unobserved heterogeneity in a pooled OLS model since any common variations in the series are not taken into account across all cross-sectional entities and over time. This will cause OLS estimates to be biased and inconsistent. In order to deal with this problem, a fixed effect model and random effects model are considered for panel data analysis. The main difference between the models is in their interpretations about unobserved individual specific effects. For a fixed effects model, u_i are taken as a fixed constants (so called fixed effect), while for a random effects model it is considered as a random variable. Another issue has been raised when considering the choice between fixed effects model and random effects model. Fixed effects regression cannot estimate the effects of time-invariant variables and the random effects estimation method can be used in this case. Furthermore, the random effects model is biased if the individual heterogeneity is correlated with the individual banks, e.g. $Cov\ (x_i\ \mu_i) \neq 0$, but fixed effects estimation will provide unbiased results. Finally, a fixed effects model is generally appropriate for a specific set of firms whereas a random effect model is an appropriate estimation method if a dataset is drawn randomly from a large population. Based on our sample choice, a fixed effect model is more appropriate since our sample has specific firms (only including banks involved into the OTD model of lending from 2006Q3 to 2009Q3). Moreover, In order to be consistent with Punanandam (2011), we also use a fixed effect model as a robustness check to examine the motivations of using OTD model of lending and to investigate the impact of OTD lending on bank credit supply. We did not use the FE model to examine its impact on bank risk-taking because the variable of preotd in the regression in chapter 7 is time-invariant and cannot be estimated by FE model. Hausman's (1978) test is carried out to test whether there is correlation between the individual effects and error terms in the models to choose between the fixed and random effects model and provide statistical support for a fixed effect model (Baltagi, 2008).

Two transformation techniques commonly used to eliminate fixed effects are 'within' estimator and 'first difference' estimator. The 'first difference' estimator eliminates the fixed effects by subtracting corresponding first-lagged values, so it could be biased and inconsistent for a small sample and the 'within' estimator is more appropriate (Arellano, 2003). The same author points out that the 'within' estimator is the most popular method in panel data analysis. Therefore, our study uses a fixed effect model with 'within' estimator as follows.

For each bank *i,* we have the average equation (4.1) over time:

$$\bar{y}_i = \alpha + \beta\bar{x}_i + u_i + \bar{\varepsilon}_i \qquad (4.4)$$

where

$$\bar{y}_i = \textstyle\sum_{i=1}^{T} y_{it}/T \qquad (4.5)$$

and so on.

Because u_i is a fixed constant over time, we can eliminate u_i if we subtract (4.2) from (4.1) and obtain the following model:

$$(y_{it} - \bar{y}_i) = \alpha + \beta(x_{it} - \bar{x}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \qquad (4.6)$$

Then the model (4.4) can be estimated by OLS and the resulting estimator of β is the 'within' estimator. In STATA, we use command 'xtreg' with the 'fe' option to run the fixed effects mode.

4.3.2 System Generalized Method of Moments (SGMM)

Besides static panel estimates, our study can also be examined by dynamic panel data models where dependent variables are affected their own lags based on previous literature (for example, Bedendo and Bruno, 2012). We use a dynamic panel data model to examine the incentives for employing the OTD model of lending and the impact of the OTD model on bank credit supply and risk taking behavior. Arellano and Bond (1991) believe that OLS is biased in dynamic panel data models and suggest that GMM is a better estimation method to address the endogeneity and fixed effect problems for dynamic panel data model.

A dynamic panel data model can be written as follows:

$$y_{it} = \alpha y_{it-1} + \beta X'_{it} + \varepsilon_{it} \qquad (4.7)$$

$$\varepsilon_{it} = \mu_i + v_{it} \qquad (4.8)$$

where i and t represent individual banks and time periods respectively. X' is a vector of explanatory variables. The error terms contain two components: the fixed effect μ_i and idiosyncratic shocks v_{it}. Two main econometric problems may arise from the above equation. First, the causality exists in both directions - those explanatory variables may be correlated with the error term, especially the endogeneity problem arising from the correlation between the lagged dependent variable and error terms. Second, time-invariant bank characteristics (fixed effects contained in the error term in equation (4.6)) may be correlated with the regressors since the fixed effects reflect heterogeneity among the individual banks (Baltagi, 2008). Therefore, The OLS estimator is biased and inconsistent in the dynamic panel data model (Baltagi, 2008). Arellano and Bond (1991) develop the Generalised Method of Moments estimator (GMM; also called

Difference GMM – DGMM) which use orthogonality conditions that exists between the lagged dependent variable and the error term to address the endogeneity problem. The Arellano – Bond estimator is specially designed for panel data with small T and large N (where N is number of groups and T is time) in order to control dynamic panel bias (Baum, 2006; Roodman, 2006) because the fixed effect contained in the error term will decline with time. Similarly, the correlation of the lagged dependent variable with the error term will be insignificant (Roodman, 2006). A first difference technique is also employed to eliminate fixed effects (Arellano and Bond, 1991). DGGM aims to minimize the objective function of the instruments and the error terms by using weighting matrices. The potential problem of DGMM is that lagged level variables could be poor instruments for first differences if the variables are close to being a random walk (Arellano and Bover, 1995). Therefore, Arellano and Bover (1995) and Blundell and Bond (1998) propose another dynamic panel approach called system GMM (SGMM) to estimate simultaneously in differences and levels. Rather than use the first difference to expunge the fixed effects in DGMM, SGMM allows the instruments to be exogenous to the fixed effects. Specifically, the difference is instrumented by lagged levels, while the equation in levels is instrumented using the first-difference of the lagged values (Roodman, 2009). Typically, the lagged dependent variables can be used as valid instruments. Lagged endogenous and predetermined regressors can also be used as instruments (Roodman, 2009). SGMM solves the problem by instrumenting the predetermined and endogenous variables with their own lags. In our model specification, the market variables and BHC dummy are treated as exogenous whereas other variables is regarded as either endogenous or predetermined variables in the regression.

We use a two-step dynamic SGMM as proposed by Arellano and Bover (1998) and Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction to address the endogeneity since the SGMM approach can reduce the finite sample bias. The reason for using SGMM is that it can overcome the weakness of DGMM with respect to inconsistent estimations on unbalanced panel data (Roodman, 2006). Our sample is extremely unbalanced since the variable of origination is not available in some quarters. Moreover, SGMM is more efficient on panels with high N/T ratio (where N is number of groups and T is time) (Arellano and Bond, 1991) and in dealing with endogeneity and fixed effects (Arellano and Bover, 1995). Our sample covers the period of 12 quarters and 743 banks in total (the N/T ratio is quite high), so we choose system GMM rather than difference GMM. Finally, the SGMM estimate has an advantage over DSGMM when the variables are random walk variables (Roodman, 2006). Since our model contains macroeconomic variables which are known for the presence of random walk statistical generating mechanisms, the SGMM is more appropriate.

The validity of SGMM results are examined based on the following statistical diagnostics. The F-test of joint significant should reject the null hypothesis that independent variables are jointly equal to zero. Furthermore, The Arellano-Bond test is employed to control for serial correlation in the residuals. The null hypotheses are that there are no first and second order correlations in the difference regression. Based on Arellano and Bond (1991), the GMM estimator requires that there is first-order serial correlation but no second-order serial correlation in the residuals. That means that the null hypothesis needs to rejected in the MA(1) test but not to be rejected in the MA(2) test.

Baum (2006) argues that the most commonly used diagnostic for SGMM to investigate the suitability of model specification is the Hansen J-statistics test. Roodman (2009) also suggest that a Sargen test is biased in two-step SGMM. Therefore, Sargen testing is not considered. Since a large number of potentially weak instruments may cause biased estimates, the validity of the instruments is tested using Hansen's J test statistic of overidentifying restrictions. There are no clear rules about how many instruments is "too many" (Roodman, 2007), but the numbers of instruments should not exceed the number of observations. Moreover, the Hansen J-test (p-value) does not reject the null at conventional significance level of 0.05 or 0.10, which indicates that the instruments are valid. Roodman (2007) suggests that a p-value should be at least as high as 0.25, otherwise it would be a concern. A perfect Hansen J-statistic with p-value equal to 0 is a sign of an inappropriate model (Roodmanm, 2009). Difference-in-Hansen test, also known C-test (Baum, 2006; Roodman, 2006), is used to evaluate the validity of subsets of instruments (i.e. levels, differenced and IV instruments). In all cases, the test statistic accepts the null hypothesis that specified variables are proper instruments, which means that the instruments are exogenous. Checking for "steady state" assumption is also used to assess the viability of instruments (Roodman, 2006). In order to make sure "steady state" assumption being held, the estimated coefficient of lagged dependent variable should have a value less than (absolute) unity (Roodman, 2007). All the test statistics above are reported at the bottom of each regression table. Table 4.1 provides a summary of model selection criteria for SGMM.

We use the command 'xtabond2' to run SGMM in the STATA. Two-step SGMM is usually utilized to obtain optimal SGMM estimator: 1) to obtain initial estimates, and 2) to estimate the optimal weighting matrix based on the first step estimation. For a small sample, one-step is more appropriate since two-step SGMM may produce biased estimation of standard error (Roodman, 2006). We choose to use two-step SGMM since our sample is relative large. Moreover, two-step SGMM can produce more efficient and precise estimates (Baltagi, 2008), because the downward-biased standard errors can be corrected by using the adjustments of Windmeijer (2005) to reduce the finite sample bias. To select the optimal number of instruments, the 'laglimits' option is used to specify the lags which are used for instruments. This option limits the maximum lag of instruments to prevent the number of instruments to be too large. Large numbers of regressions are estimated by choosing different lower and upper lag-limits. The optimal regression must satisfy all the criteria discussed above (as listed in Table 4.1) and has highest p-value of Hansen J-test.

Table 4.1: Model Selection Criteria for SGMM

Criteria	Requirements Descriptions
F-test	Reject the null hypothesis that independent variables are jointly equal to zero.
Arellano-Bond test for serial correlation	First-order serial correlation but no second-order serial correlation in the residuals (Arellano and Bond, 1991)
Sargen Test	Sargen test is biased in two-step SGMM (Roodman, 2009). Therefore, Sargen test is not considered.
Hansen J-statistic and Difference-in-Hansen Statistic	The p-value of Hansen test should be higher value than conventional significance level of 0.05 or 0.10, at least as high as 0.25 is suggested by Roodman (2007), otherwise it would be a concern. A perfect Hansen J-statistic with p-value equal to 0 is the sign of inappropriate model (Roodmanm, 2009).
Steady state	The estimated coefficient of lagged dependent variable should have a value less than (absolute) unity (Roodman, 2007), otherwise SGMM is invalid.
Number of instruments	The number of instruments should not exceed the number of observations (Roodman, 2009)

Source: Roodman (2006), Roodman (2009), Arellano and Bond (1991)

4.4 Measuring the OTD Model of Lending

Followed by Purnanandum (2011), we obtain two key variables from Call Reports to describe mortgage activities in the context of origination-to-distribute: (1) the origination of 1–4 family residential mortgage loans for resale and (2) the 1–4 family residential mortgage loans actually sold. We define origination as a ratio of loan origination for resale during the quarter scaled by the beginning of quarter total mortgage loans to proxy the desired level of participation in the OTD model. We use mortgage loans actually sold as a fraction of total mortgage loans at the beginning of each quarter to measure the actual level of involvement in OTD. The OTD practices are estimated by the following model:

$$\Delta \ln(loansale)_{i\,t} = \alpha_i + \beta_1 Origination_{i\,t} + \beta_2\, NPL_{i\,t-1}$$

$$+ \beta_3 Cost\ of\ funding_{i\,t-1} + \sum_{j=1}^{5} \gamma_j\, X_{j\,t-1}$$

$$+ \sum_{k=1}^{2} \varphi_k\, \Delta M_{k\,t} + \beta_4 \Delta ln(loansale)_{i\,t-l} + \varepsilon_{1t}$$

$\Delta ln(loansale)$ is measured as bank mortgage loan sales as a fraction of total mortgage loans at the beginning of the quarter. Origination is the ratio of mortgage loans origination to the beginning of period total mortgage loans. NPL is measured by non performing mortgage loans of bank divided by total mortgage loans. NPL is measured as the ratio of non-performing mortgage loans of bank to total mortgage loans to measure the quality of mortgage loans on the balance sheet.[17] Cost of funding is the ratio of interest expense to total liabilities. X_{jt-1} is denoted by a set of control variables, such as total assets, deposits, capitals, liquid assets and C&I loans. Total asset is a nature logarithm of total assets at the beginning of quarter. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. C&I loans is the ration of commercial and industrial loans to total assets. Summary statistics for our key variables are provided in the table 4.2.

[17] We consider 1-4 family residential mortgage loans that are past due 30 days or more and are non-accruing as non-performing loans.

Table 4.2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Loan sales	6181	0.716	0.589	0	-1.829
Origination	7631	0.299	0.552	0	3.328
NPL	8916	0.022	0.023	0	0.122
Cost of funding	8916	0.018	0.009	0.003	0.040
Ln(TA)	8916	13.997	1.442	11.226	18.749
Capital ratio	8916	0.112	0.030	0.071	0.254
Deposits ratio	8916	0.065	0.044	0.002	0.232
Liquid ratio	8916	0.099	0.073	0.013	0.389
C&I loans	8916	0.112	0.068	0	0.341

We next plot several charts to describe the OTD activities and mortgage loan default. Figure 4.1 demonstrates the quarterly average percentage of mortgage origination for resale as a fraction of the beginning of the quarter total mortgage loans. This ratio measures the level at which banks tend to be involved in OTD. The ratio slightly decreases in the first three quarters, in line with investors' being concerned about a house price bubble in early 2007. As expected, OTD business was squeezed due to illiquid market conditions after 2007Q3 from 33% to 25% in 2007Q3.

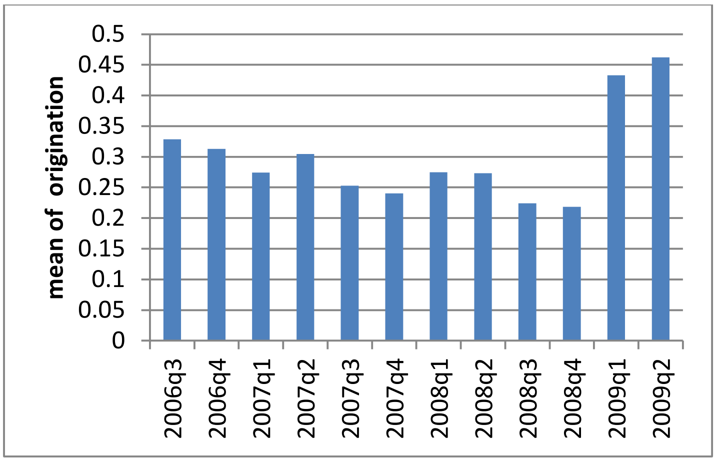

Figure 4.1: Mortgage originated for distribution over time

The figure 4.1 shows the ratio of originated OTD loans to total mortgages in each quarter. We plot the average value of this ratio across all banks from 2006Q3 to 2009Q2.

Figure 4.2 plots the quarterly average of 1-4 family residential mortgage loans sold scaled by the beginning of the quarter total mortgage loans. This shows the extent of mortgage loans which were actually offloaded from balance sheets in the given quarter. It is clearly seen that there is a significant decline in loan sale since 2007Q2 to 21% in the 2008Q4. Since the Federal Reserve Bank required Government-Sponsored Enterprises (GSEs) to buy mortgage loans to pump liquidity into financial markets when the market was not liquid, there is a dramatically increase in OTD lending after 2008Q4 from 22% to 46% in 2009Q2. We also can see a similar trend for loan sale from 21% to 44% in the Figure 4.2. In a word, the first two graphs show the extent of mortgage loan origination desired to be sold and mortgage loan actually sold to third parties over this period.

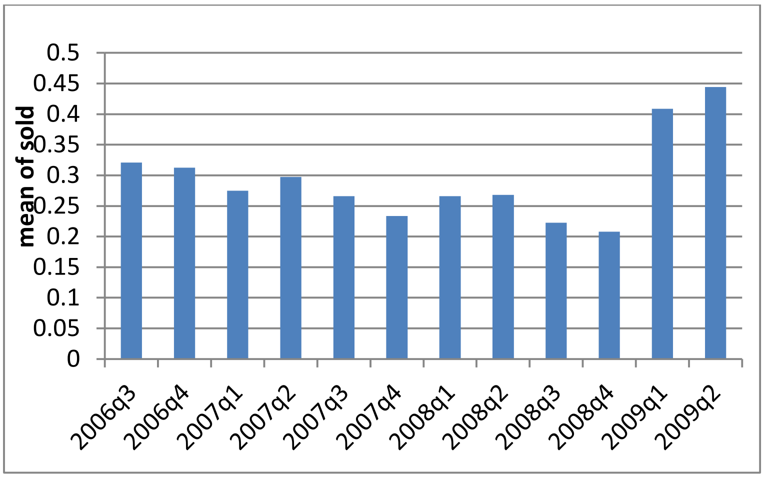

Figure 4.2: Mortgage actually sold over time

The figure 4.2 shows the OTD loans actually sold as a fraction of mortgages outstanding at the beginning of the quarter. We plot the average value of this ratio across all banks from 2006Q3 to 2009Q2.

In Figure 4.3, we plot the average non-performing loans on 1–4 family residential mortgage loans as a fraction of total 1-4 family residential mortgage loans at the beginning of the quarter. From this chart, the quarterly non-performing loans ratio increased gradually after 2007Q2 up to 3.8% of total mortgage loans at 2009Q2. Figure 4.4 shows the average percentage net-charge offs on total 1-4 family residential mortgage loans in the each quarter. Not surprisingly, the net-charge offs have increased significantly after the second quarter of 2007, especially a sharp increase up to 0.4% from 2008Q1 to 2008Q4. This is consistent with the common proposition that banks extensively involved in the OTD model have higher default rates after the financial crisis.

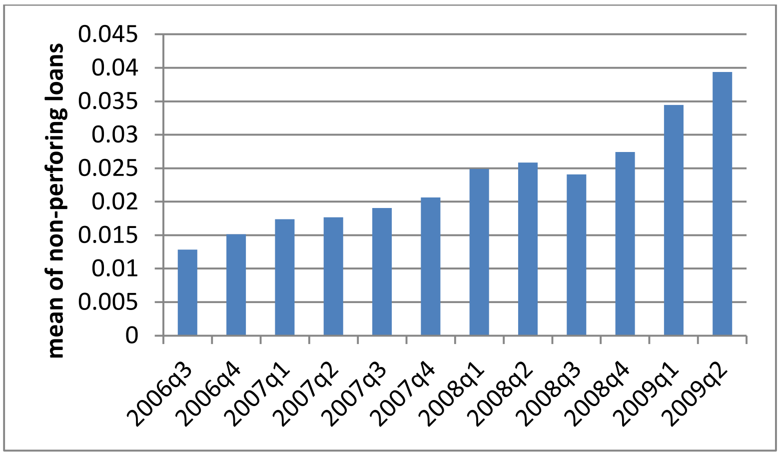

Figure 4.3: Non-performing mortgage loans over time

The figure 4.3 shows non-performing mortgage loans as a percentage of mortgages outstanding at the beginning of the quarter. We plot the average value of this ratio across all banks from 2006Q3 to 2009Q2.

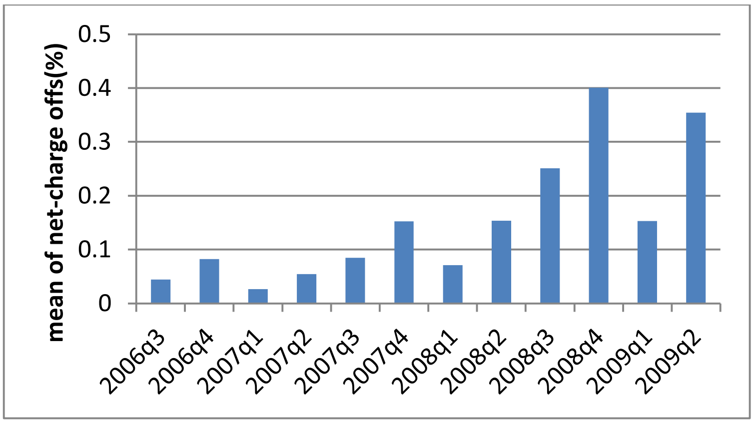

Figure 4.4: Mortgage Net-charge offs over time

The figure 4.4 shows average percentage net-charge offs on outstanding mortgage in the each quarter. We plot the average value of this ratio across all banks from 2006Q3 to 2009Q2.

4.5 Summary

This chapter presents the source of data, methods of data collection, research sample and data analytical techniques employed in this study. Individual US bank-level data are mainly obtained from Call report. Macro data, the real GDP and House Price Index (HPI), are collected from the U.S. Bureau of Economic Analysis and the Federal Housing Finance Agency, respectively. We show that Fixed Effects and SGMM estimators are the most appropriate data and we consider both methods in our study (Fixed Effects as a robustness test). Finally, this chapter describes measures of OTD model of lending and plots several figures with variables we use in the model specification. The summary statistics of variables and several figures about our key variables are provided in the chapter.

Chapter 5

The Incentive Structure for the OTD Model of Lending

5.1 Introduction

The literature describes several reasons why banks might need to use the OTD model. One motivation is regulatory arbitrage. Banks sell loans in order to offload them from their balance sheets, reducing expected regulatory costs (Pennacchi, 1998), lowering the cost of capital by saving reserves to meet capital requirements set up by regulators (James, 1987; Gorton and Pennacchi, 1995). A second motivation is risk sharing or transfer. Banks can transfer risk to from the banking system to other sectors to improve risk sharing since loans can be sold off from balance sheet (Allen and Carletti, 2006; Bannier and Hänsel, 2007; Affinito and Tagliaferri, 2010). Last but not the least, this model also provides an additional source of funding to financing bank loans and liquidity (Diamond and Rajan, 2001; Loutskina, 2011), Notwithstanding any positive effects, since the financial crisis of 2007 high default rates have caused doubts about securitized products. Brunnermeier (2009) suggests that banks participating via the OTD lending model had excessive credit supply and increased default rate due to lower incentive to monitor borrowers, contributing to the financial crisis. Empirical evidence has started to question the OTD model and the actual role played by OTD model of lending is widely debated. This chapter aims to understand the determinants of OTD lending and address following open questions. What motivates banks to be engaged in the OTD lending? Did banks have the similar incentives to employ the OTD lending vary across banks' involvement in the OTD model and bank size? How did regulators monitor these banks? Addressing these issues has implications for policy makers. First, it gives a direct assessment on the incentive for employing OTD model among low- and high-OTD banks. Secondly, it provides a better understanding of OTD activities, knowing clearly about the benefits and drawbacks of OTD model for both low- and high-OTD banks. Finally, it helps bank regulators to examine whether Basel III and the Dodd-Frank Act are suited to re-establish a sustainable OTD framework.

We first divide our sample into two subsamples, low-OTD banks and high OTD banks based on the average value of origination to resell to total mortgage loans and examine whether these two groups have similar incentives to use OTD lending from 2006Q3 to 2009Q2. Consistent with Purnanandam (2011), banks that originated more OTD loans tend to sell loans from their balance sheets for both low- and high-OTD banks. Our results also show that another incentive of using OTD model is that banks with higher share of risky mortgage portfolios are more likely to be engaged in the model for both two groups. Moreover, the motivations for using the OTD model may differ between low- and high OTD banks. Our results show that high-OTD banks resort to the OTD model as a source of funding in addition to their usual sources, such as deposits and liquid assets, when they face higher funding costs. Besides that, we also find high-OTD banks use the OTD model as a liquidity provider when they face liquidity constraints. We then divide banks into two groups, small banks and large banks, based on the value of total assets. Our results indicate that capital arbitrage becomes more important for small banks as they might not have enough capital and are more likely to employ the OTD lending to alleviate capital requirements.

We aim to shed more light on the motivation for using the OTD model of lending by comparing low- and high-OTD banks. Our results are closely linked to Purnandam, (2011) Loutskina (2011), Affinito and Tagliaferri (2010), Bedendo and Bruno (2012) and Casu et al. (2013) suggest that banks with more originated OTD loans, less liquid assets, larger amount of non-performing loans and higher cost of fund tend to use OTD lending Moreover, the incentives to be involved in the OTD model may also vary across bank size and business cycle. Our results support a regulatory arbitrage hypothesis for small banks (James, 1987; Gorton and Pennacchi, 1995; Pennacchi, 1998; Ambrose et al., 2005;

Acharya et al., 2013; Demyanyk and Loutskina, 2013) that the OTD model can be used to reduce regulatory capital requirements as they are less capitalized. Second, our research focuses on one asset class in the OTD model, 1-4 family residential mortgage loans, which account for the majority of OTD lending whereas other studies pay more attention to a single instrument of the OTD model, normally loan sale or securitization. In particular, we examine driving forces for employing the OTD lending at the frontend of securitization channel at originating bank level. Third, we extend the research period until the peak of the financial crisis and its aftermath and examine whether the role of OTD lending changed during the financial turmoil, while previous studies mainly focus on the motivations of OTD lending during the pre-crisis period.

The rest of the chapter is organized as follows. We describe our data and methodology in Section 5.3, and empirical specification in Section 5.4. In Section 5.5, we show some descriptive statistics of variables which are used in the regressions, and then some empirical results on the determinants of OTD lending are shown in Section 5.6. Section 5.7 concludes the chapter.

5.2 Hypothesis Development

In this chapter, we examine the motivations for using the OTD model suggested in the literature across different intensities of involvement in the OTD model and across bank size. To conduct our analysis, we divide our sample into low-OTD and high-OTD banks, based on the average value of origination for resale. We estimate the model separately to capture difference in the incentives for using OTD model of low- and high-OTD banks. Moreover, we also divide banks into small and large banks based on the value of total assets to examine whether they have different motivations for engagement in OTD lending.

After banks originate mortgage loans and intend to sell these loans, they usually stay on the balance sheet of those banks for two or three quarters before being sold off in the sales pipeline (Gordon and D'Silva 2008). Purnanandam (2011) shows that banks with more originated OTD loans seem to get involved in the OTD model of lending, so we suggest that banks tend to participate in the OTD model of lending to sell originated mortgage loans which are intended for resale. Affinito and Tagliaferri (2010) find that banks with higher level of non-performing loans are willing to be involved in the OTD market. Bedendo and Bruno (2012) also show that banks with lower quality loans are driven to be active in the credit risk transfer activities. Therefore, we suggest that banks with risky mortgage portfolios tend to sell more loans off balance sheets.

H1: banks with more OTD loans are more likely to sell these loans in the secondary market.

H2: Banks with more non-performing mortgage loans have more incentive to be engaged into the OTD model of lending.

In the traditional banking framework, banks mainly use deposits to finance credits. OTD model allows banks to sell loans to the secondary market. After banks sell off mortgage loans from their balance sheets, they can rise new funding to increase availability of source of funds, making banks less reliant on the traditional sources of funding. Loutikina (2011) suggests that this provides banks with an additional source of funding to alleviate constraints from external cost of funds shocks. Therefore, we suggest that banks use OTD model of lending when they face cost of funds shocks. Moreover, OTD lending can provide liquid loans to finance banks' liquidity needs. More available funding can be used to finance their new loans or meet their liquidity requirements. Loutikina (2011) argues that banks that are active in the OTD market hold fewer liquid assets and can meet their liquidity needs through selling loans. Therefore, we suggest that banks would like to use

OTD model to provide liquidity when they lack liquidity or face liquidity constraints during financial turmoil.

H3: Banks engage in OTD lending when they face high cost of funding.

H4: Banks facing liquidity constraints or having liquidity shortfalls are more likely to employ the OTD model in order to obtain liquidity.

Banks need to hold a minimum level of regulatory capital for making loans. The Basel II capital regulatory framework required banks to hold higher level of capital for loans made to riskier borrowers in order to align more properly their portfolios with different risk levels. However, the OTD model allows banks to offload some proportions of their loan portfolios from their balance sheets and to lend to more risky borrowers to increase expected return without changing capital requirements. Therefore, we suggest that banks with capital constraints would be involved in the OTD model to reduce capital requirements.

H5: Banks with less capital or with an incentive of regulatory capital arbitrage would use OTD model to release capital.

5.3 Descriptive Statistics

Table 5.1 reports descriptive statistics for banks used in our classification. The first three columns show the numbers of banks and the numbers of low and high-OTD banks used in our sample by quarter. It also reports average bank size of low-OTD and high-OTD banks and their OTD practices in each quarter. Obviously, the average total assets of high-OTD banks are much larger than those of low-OTD banks. It also can be clearly seen that the average OTD loans ratio for banks highly engaged into OTD model is much larger than those with lower involvement in the OTD model. 70% of total 1-4 family residential mortgage loans are originated and intended to be sold off from balance sheet for high-OTD banks while only 20% OTD 1-4 family mortgage loans for low-OTD banks are desired to be sold in 2009Q2. Moreover, we report the number of small and large banks involved in the OTD model. The average OTD loans ratio for small banks is much higher than that for large banks, 77% for small banks and 26% for large banks respectively, which indicates that most small banks are intensively involved in the OTD model. This also provides evidence to explain why small banks are more risky than large banks in the next chapter.

Table 5.1: Descriptive statistics

Quarter	Numbers of banks			Average bank size		Average OTD loans	
	Total	Low OTD	High OTD	Low OTD	High OTD	Low OTD	High OTD
2006Q3	447	200	247	2299	17305	0.147	0.476
2006Q4	540	239	301	2383	18134	0.132	0.456
2007Q1	619	297	322	2407	18456	0.109	0.426
2007Q2	633	310	323	2452	19022	0.124	0.477
2007Q3	645	315	330	2586	20245	0.118	0.381
2007Q4	657	319	338	2678	21045	0.102	0.370
2008Q1	660	317	343	2745	21803	0.105	0.432
2008Q2	680	327	353	2797	21720	0.098	0.436
2008Q3	692	332	360	2847	22839	0.071	0.365
2008Q4	693	329	364	2956	23435	0.069	0.354
2009Q1	673	312	361	3001	22748	0.150	0.678
2009Q2	692	332	360	2960	22546	0.202	0.702
	Total	Small	Large	Small	Large	Small	Large
2006Q3	447	182	265	471	20779	0.613	0.133
2006Q4	540	208	332	473	21104	0.563	0.156
2007Q1	619	261	358	474	21003	0.456	0.142
2007Q2	633	268	365	478	21269	0.487	0.171
2007Q3	645	278	367	480	22239	0.402	0.140
2007Q4	657	276	381	478	22365	0.388	0.134
2008Q1	660	271	389	485	22920	0.456	0.149
2008Q2	680	285	395	489	22604	0.445	0.149
2008Q3	692	289	403	489	23242	0.367	0.121
2008Q4	693	288	405	499	23766	0.361	0.117
2009Q1	673	264	409	501	22954	0.740	0.235
2009Q2	692	277	415	497	22416	0.767	0.258

Notes:
1. The table reports the number of banks examined between 2006Q3 and 2009Q2, we segregate these banks into low and high OTD banks based the average value of origination for resell across all quarters.
2. Bank size is computed as the average of total assets in given quarter, reported in millions.
3. Average OTD loans ratio is measured as quarterly average of 1-4 family residential mortgage loans intended for resell divided by total 1-4 family mortgage loans.

5.4 Model Specification (SGMM Estimations)

In order to build our model, we include important determents of loans sales activities based on previous literature. First, Purnanandam (2011) suggests that banks with more OTD mortgage loans tend to sell these loans, so mortgage OTD lending is included so as to measure the OTD level that banks tend to achieve.[18] Secondly, Non-Performing Loans (NPLs), a proxy for mortgage loan quality, is measured as the ratio of the non-performing loans of 1-4 residential mortgage loans to total mortgage loans.[19] Last but not least, cost of funding, measured by the cost of deposits, which is one of the driver forces of using OTD model (Bendendo and Bruno, 2012; Affinito and Tagliaferri, 2010). Loutskina (2011) suggests that the OTD model can be used as an external source to provide liquidity when banks suffer cost of funds shocks. In addition, the regression also includes a set of control variables which have an influence on OTD activities.

[18] The OTD data are divided into two categories: retail origination and wholesale origination. We divide the sum of retail and wholesale origination by the beginning of the quarter total assets as a measure of OTD in our analysis.
[19] We consider 1-4 family residential mortgage loans that are past due 30 days or more and are non-accruing as non-performing loans.

The model is estimated as follows:

$$\Delta ln(loansale)_{it} = \alpha_i + \beta_1 Origination_{it} + \beta_2 NPL_{it-1} + \beta_3 Costoffunding_{it-1} + \sum_{j=1}^{5} \gamma_j X_{jt-1} + \sum_{k=1}^{2} \varphi_k \Delta M_{kt} + \beta_4 \Delta ln(loansale)_{it-l} + \varepsilon_{1t}$$

The dependent variable measures the quarterly change of bank mortgage loan sales as a fraction of total mortgage loans at the beginning of the quarter. Origination is the ratio of mortgage loans origination to the beginning of period total mortgage loans. NPL is measured by non performing mortgage loans of 1-4 family residential mortgage loans divided by total mortgage loans.[20] Cost of funding is the ratio of interest expense to total liabilities.

X_{jt-1} is denoted by a set of control variables, such as total assets, deposits, capitals, liquid assets and C&I loans. Total asset is the natural logarithm of total assets at the beginning of quarter. Loan ratio is the share of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand

[20] We take 1-4 family residential mortgage loans as total mortgage loans for granted.

deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of total assets.

In addition, we also add a BHC dummy variable, equal to one if the bank is part of a single-bank holding company, equal to two if it is affiliated with a multi-bank holding company, and zero otherwise (Ashcraft, 2008). M_{it} is the quarterly change in macroeconomic variable (quarterly changes in the logarithms of the real GDP of US and the house price index). To deal with endogeneity problems which arise from loan sales affected by previous OTD activities, we use lagged changes in the explanatory variables and add lagged dependent variables (with two lags). Moreover, SGMM solves the problem by instrumenting the predetermined and endogenous variables with their own lags. In the SGMM estimation, the lagged dependent variables can be used as valid instruments. Lagged endogenous and predetermined regressors can also be used as instruments (Roodman, 2009). In our model specification, the market variables and BHC dummy are treated as exogenous whereas other variables is regarded as either endogenous or predetermined variables in the regression.

In line with previous studies, the coefficient of origination tends to be significantly positive, which indicates that an increase in loan sales can be explained by an increase in OTD mortgage loans. We expect a positive and significant coefficient on the non-performing loans term, which implies that deterioration of mortgage loans quality leads to an increase in loan sales. We also expect that the coefficient of cost of funds is significantly positive; indicating that banks faced with higher funding cost will tend to sell more mortgage loans as a source of additional funding. The coefficient of capital ratio is expected to negative as the OTD lending can be used to release some capitals when banks are lack of capitals. The expected sign of the coefficients of liquidity ratio is also negative since banks seem to use the OTD model of lending to meet liquidity needs.

5.5 Empirical Results

Table 5.2 provides estimation to show why banks would want to use the OTD model of lending. In line with Purnanandam (2011), we observe a significant and positive coefficient on origination term for both low- and high OTD banks in Models 1 and 3. This indicates that banks with more OTD mortgage loans are more likely to sell these loans. As expected, the coefficient on the NPL term is significantly positive for both low- and high-OTD banks, which shows that riskier mortgage loans portfolios increase banks' incentive to be engaged in OTD business model and may have an incentive to sell off lower quality mortgage loans (Affinito and Tagliaferri, 2010; Agarwal et al., 2012). These results are significant and positive for both low OTD banks in Model 1 and high OTD banks in Model 3. Since large banks are more likely to have a different business model (Purnanandam, 2011), we delete banks with more than $10 billion total assets. The results remain significant after we exclude large banks from our sample in Models 2 and 4.

We also find that there is a positive relationship between the cost of funding and loan sales, as indicated by a significant and positive coefficient on the estimation of cost of funding for high-OTD banks in Model 3. This is consistent with Loutskina (2011) that the OTD model can provide an additional source of funding when facing funding constraints. The results, displayed in Models 3 and 4, suggests that banks suffering liquidity constraints tend to employ the OTD model as a liquidity buffer since the coefficients on the term of liquid ratio are negative and significant. In addition, the coefficient on the commercial and industry loans (C&I) is significant and negative as it is shown in Model 1 and Model 2, which indicates that low-OTD banks with lower amount of C&I loans are more likely to engage in the model, getting funds from selling loans to invest in more profitable business.

In addition, we divide banks into two groups, small banks and large banks. We define small banks as those with total assets less than 1 billion and large banks with total assets more than 1 billion, and then we estimate the model separately to capture differences in the motivations of OTD practices across different bank size. Estimation results are provided in the Table 5.3. Consistent with our previous result, there is a significant and positive coefficient on the term of Origination in Model 1 and Model 2, which suggests that both small and large banks tends to sell originated OTD loans. Moreover, it can be clearly seen that the coefficient of non-performing loans is positive and significant in Model 1 and Model 2, which indicates that both small and large banks with risky mortgage portfolios seem to sell more loans.

For small banks, cost of funding is positively related to loan sale since the coefficient shown in the Model 1 is positive, which means that small banks seek to use OTD lending when they face higher cost of funding, but we cannot find a significant relationship in large banks. This may be because large banks have various source of funding and are less likely to face higher cost of funding relative to small banks. As expected, the coefficient of capital ratio is positive and significant for small banks, as reported in the Model 1, which is consistent with the regulatory arbitrage hypothesis that capital-constrained banks tend to engage in OTD lending to alleviate capital requirements. However, the result is not significant for large banks as it is shown in the Model 2. Arbitrage capital becomes more important for small banks because they are more likely to be less capitalized. Our results also show that loan sale is negatively related to the liquid assets for small banks, as indicated by a negative and significant coefficient on the liquid ratio term in Model 1. This is consistent with the proposal that banks involved into OTD lending tend to hold less liquid assets and can meet their liquidity needs through selling loans (Loutikina, 2011). Consequently, it is important to point out that releasing funding and capital constraints and enhancing liquidity for small banks to participate in the OTD lending.

Table 5.2: SGMM estimations for the determinants of OTD lending of low- and high-OTD banks

This table reports the estimates for determinants of OTD lending of low- and high-OTD banks from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. C&I ratio is computed as commercial and industry loans divided by total assets. The model is estimated by system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) Low-OTD banks excluding large banks	(3) high-OTD banks	(4) high-OTD banks excluding large banks
Origination	1.202***	1.063***	0.759***	0.703***
	(3.17)	(3.32)	(8.94)	(8.02)
Non perforiming loans	13.378***	13.435***	6.404***	7.364***
	(4.32)	(4.36)	(3.45)	(3.77)
Cost of funding	-0.831	0.547	5.674***	6.595***
	(-0.42)	(0.26)	(4.89)	(5.14)
LogTA	0.162	0.361	-0.051	-0.031
	(0.35)	(0.78)	(-0.60)	(-0.26)
Capital ratio	-7.714	-6.607	-1.696	-3.107
	(-1.61)	(-1.48)	(-0.86)	(-1.59)
Deposit ratio	-2.120	-1.481	-0.879	-2.241*
	(-0.87)	(-0.75)	(-0.77)	(-1.95)
Liquid ratio	-1.478	-2.742**	-1.777**	-1.331*
	(-1.25)	(-2.42)	(-2.34)	(-1.70)
C&I loans	-9.808***	-8.468***	0.599	-0.379
	(-2.83)	(-2.72)	(0.33)	(-0.20)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
cons	-0.091	-2.892	0.979	0.978
	(-0.01)	(-0.45)	(0.76)	(0.55)
Observations	1908	1809	2788	2409
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.647	0.133	0.493	0.383
Hansen test(p-value)	0.424	0.862	0.66	0.747

Table 5.3: SGMM estimations for the determinants of OTD lending of small and large banks

This table reports the estimates for determents of using OTD model of lending of small and large banks from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. C&I ratio is computed as commercial and industry loans divided by total assets. The model is estimated by system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Small banks	(2) Large banks
Origination	0.950***	0.994***
	(9.31)	(4.49)
Non performiming loans	3.672**	15.625***
	(2.35)	(5.61)
Cost of funding	6.378***	1.377
	(4.17)	(0.99)
LogTA	0.026	-0.107
	(0.08)	(-0.45)
Capital ratio	-6.420**	-3.566
	(-2.34)	(-0.84)
Deposit ratio	1.110	-2.540
	(0.89)	(-1.01)
Liquid ratio	-2.174***	-1.479
	(-2.77)	(-1.41)
C&I loans	-1.767	-7.083*
	(-1.08)	(-1.94)
BHC flag	Yes	Yes
Market controls included	Yes	Yes
Lagged dependent variables included	Yes	Yes
cons	0.506	2.765
	(0.11)	(0.76)
Observations	1820	2768
Wald test (p- value)	0.000	0.000
MA(1) (p-value)	0.000	0.000
MA(2) (p-value)	0.943	0.648
Hansen test(p-value)	0.584	0.382

From the second quarter of 2007, the value and liquidity of structured products were doubted and credit rating agencies downgraded mortgage-backed securities - losses from these debt securities rose dramatically in the following year. The increasing numbers of mortgage loan defaults and securities losses eventually contributed to the collapse of several financial institutions, including Fannie Mae and Freddie Mac, the American International Group, Inc. (AIG) and Lehman Brothers; then the meltdown expanded quickly across the whole financial market. This situation was slightly alleviated at the beginning of 2009 when private capital was brought back to banking system during the stress testing of large banks (Cornett et al. 2011). We would like to examine whether OTD model of lending still can be used during financial downturn.

Since the Federal Reserve Board (2010) suggests that the residential mortgages market tightened considerably over most of the period 2007:Q3–2009:Q2, we add a dummy variable *After* which is equal to one after 2007Q3 and zero otherwise, and use Origination interacted with *After* dummy to isolate the impact from Pre-crisis period. We also want to investigate whether banks could still use the OTD model when financial conditions were at their most severe in the fourth quarter of 2008. In order to conduct our tests, we include a dummy variable *Crisis* which is equal to one for the fourth quarter of 2008 and zero otherwise, and use Origination interacted with *Crisis* dummy to isolate the impact from the other quarters. The modified model is as follows:

$$\begin{aligned}\Delta \ln(loansale)_{it} &= \alpha_i + \beta_5 Origination_{it} + \beta_6 Origination_{it} * After \\ &+\beta_7 NPL_{it-1} + \beta_8 Costoffunding_{it-1} + \sum_{j=1}^{5} \delta_j X_{jt-1} \\ &+ \sum_{k=1}^{2} \theta_k \Delta M_{kt} + \beta_9 \Delta \ln(loansale)_{it-i} \\ &+\beta_{10} After + \varepsilon_{2t}\end{aligned}$$

The estimation results are shown in Table 5.4. It can be observed that there is a significant and positive coefficient of iteration terms in the Model 2, which indicates that high-OTD banks can still offload originated OTD loans during the financial crisis which were planned for resale. In addition, we also can get similar findings for small and large banks as the coefficients on interaction terms, reported in Model 3 and Model 4 are positively significant. This might be explained by Federal Reserve Banks preserving the liquidity of OTD to help banks alleviate funding shocks (Bendendo and Bruno, 2012). The results remain significant when the financial conditions are most severe in 2008Q4 which is shown in the Table 5.5. However, the coefficients of iteration terms are not significant for low-OTD banks, as reported in the Mode l. This is consistent with a significant drop in selling f originated OTD loans from balance sheets due to illiquid market conditions during the financial downturn.

Table 5.4: System GMM estimations for the determinants of OTD lending with crisis dummies

This table reports the estimates of changes of loan sale on mortgage origination, non-performing loans, cost of funding and bank characteristics from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. C&I ratio is computed as commercial and industry loans divided by total assets. *After* is a dummy variable which is equal to one for the fourth quarter of 2008 and zero otherwise. The model is estimated by system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) high-OTD banks	(3) Small banks	(4) Large banks
Origination	0.952**	0.657***	0.830***	0.767***
	(2.03)	(7.28)	(8.22)	(3.54)
Origination*After	0.357	0.155***	0.137**	0.195**
	(1.43)	(3.37)	(2.45)	(2.27)
Non-performing loans	11.802***	5.553***	2.550*	12.637***
	(3.97)	(2.84)	(1.67)	(4.52)
Cost of funding	-4.319*	5.653***	4.666**	1.856
	(-1.65)	(4.11)	(2.42)	(0.99)
LogTA	0.039	-0.014	-0.203	-0.032
	(0.11)	(-0.21)	(-0.60)	(-0.28)
Capital ratio	-5.253	-1.430	-2.521	-6.286
	(-1.11)	(-0.68)	(-0.99)	(-1.56)
Deposit ratio	-2.246	-0.618	0.947	-2.699
	(-0.97)	(-0.50)	(0.75)	(-1.23)
Liquid ratio	-0.663	-1.558**	-1.491*	-1.652
	(-0.55)	(-2.03)	(-1.95)	(-1.50)
C&I loans	-8.266**	0.710	-2.486	-7.342**
	(-2.56)	(0.40)	(-1.42)	(-2.28)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
Time dummy included	Yes	Yes	Yes	Yes
cons	1.011	0.461	2.973	2.172
	(0.21)	(0.45)	(0.67)	(1.19)
Observations	1908	2788	1820	2768
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.311	0.448	0.894	0.928
Hansen test(p-value)	0.376	0.655	0.508	0.587

Table 5.5: The motivations of OTD model of lending with 2008Q4

This table reports the estimates of changes of loan sale on mortgage origination, non-performing loans, cost of funding and bank characteristics from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Cost of funding is the ratio of interest expense to beginning of quarter liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. C&I ratio is computed as commercial and industry loans divided by total assets at beginning of quarter. *After* is a dummy variable which is equal to one for the fourth quarter of 2008 and zero otherwise. The model is estimated by system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level.

	(1) Low-OTD banks	(2) Low-OTD banks excluding large banks	(3) high-OTD banks	(4) high-OTD banks excluding large banks
Origination	1.235***	1.160***	0.853***	0.962***
	(2.97)	(3.12)	(8.26)	(8.80)
Origination*Crisis	0.168	0.249	0.119**	0.122**
	(0.37)	(0.56)	(2.06)	(2.05)
Non-performing loans	13.023***	12.891***	6.347***	6.962***
	(4.31)	(4.59)	(3.32)	(3.75)
Cost of funding	-0.197	0.505	6.358***	6.498***
	(-0.09)	(0.22)	(5.36)	(4.73)
LogTA	0.350	0.238	0.011	0.072
	(0.79)	(0.54)	(0.13)	(0.52)
Capital ratio	-7.931	-8.741**	-0.242	-0.174
	(-1.64)	(-1.98)	(-0.11)	(-0.07)
Deposit ratio	-2.450	-1.471	-0.755	-0.863
	(-0.97)	(-0.63)	(-0.60)	(-0.81)
Liquidity ratio	-1.744	-2.260**	-1.809**	-1.068
	(-1.42)	(-2.01)	(-2.23)	(-1.19)
C&I loans	10.804***	-9.507***	1.338	3.374
	(-2.80)	(-3.32)	(0.73)	(1.55)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
Time dummy included	Yes	Yes	Yes	Yes
cons	-2.473	-0.828	-0.192	-1.331
	(-0.42)	(-0.14)	(-0.15)	(-0.66)
Observations	1908	1809	2788	2409
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.676	0.730	0.501	0.665
Hansen test(p-value)	0.429	0.471	0.657	0.292

5.6 Robustness Tests

Following Punanandam (2011), we then use the fixed effect model as a robustness test. It is important to note that a fixed effect model will be biased as this estimation strategy suffers from lagged dependent variable (LDV) bias since the fixed effect is correlated with the LDV. Therefore, lagged dependent variables are not included in the fixed effect model. The Hausman test indicates that there is correlation between regressors and heterogeneity effects (i.e., fixed effects). Thus, Ordinary Least Square (OLS) estimations based on the 'within' differencing technique are used to address the fixed effects.

The model is estimated as follows:

$$\Delta ln(loansale)_{it} = \alpha_i + \beta_{11} Origination_{it} + \beta_{12} NPL_{it-1}$$

$$+\beta_{13}(Cost\ of\ funding)_{it-1} + \sum_{j=1}^{5} \vartheta_j\, X_{jt-1}$$

$$+\sum_{h=1}^{2} \rho_h\, \Delta M_{kt} + \varepsilon_{3t}$$

Table 5.6: Fixed effect estimations for the determinants of OTD lending

We show fixed effects regressions of changes of loan sale on mortgage origination, non-performing loans, cost of funding and bank characteristics from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. C&I ratio is computed as commercial and industry loans divided by total assets. All standard errors, clustered at the bank level, are reported in parentheses. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) high-OTD banks	(3) Small banks	(4) Large banks
Origination	1.031***	0.507***	0.506***	0.762***
	(4.10)	(10.71)	(9.85)	(5.06)
Non-performing loans	4.026***	1.460**	2.186***	3.090***
	(4.58)	(2.12)	(3.18)	(3.22)
Cost of funding	0.537	2.929***	5.675***	-0.462
	(0.35)	(3.03)	(5.24)	(-0.38)
LogTA	0.349**	0.218*	0.315**	0.225*
	(2.47)	(1.71)	(2.24)	(1.72)
Capital ratio	-0.098	0.098	-1.294	0.925
	(-0.07)	(0.12)	(-1.46)	(0.76)
Deposit ratio	0.203	-0.406	0.260	-0.344
	(0.21)	(-1.10)	(0.53)	(-0.40)
Liquid ratio	-0.508	-0.309	-0.384	-0.569
	(-1.15)	(-0.88)	(-1.07)	(-1.39)
C&I loans	-0.354	1.389**	1.028	-0.007
	(-0.43)	(2.25)	(1.52)	(-0.01)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
cons	-5.100**	-3.151*	-4.144**	-3.494*
	(-2.51)	(-1.69)	(-2.24)	(-1.74)
Observations	2646	3534	2567	3613
R^2	0.143	0.239	0.287	0.131

Table 5.6 shows the fixed effect estimations for Consistent with our results from SGMM estimation, banks seek to sell originated OTD loans that are intended for resell in the pipelines as the coefficients of origination terms are significant and positive in the all regressions. We also document that the coefficients of non-performing loans are significantly positive in the fixed effect estimations, which shows that banks with poor mortgage loans performance tend to sell mortgage loans. Similar to the SGMM estimation results, there is a positive and significant relationship between cost of funding and loan sale for high OTD banks and small banks in Model 2 and Model 3 respectively, which indicates that they will be engaged in the OTD model of lending when they face high funding cost. However, we cannot find that loan sale is negatively affected by liquid assets for high-OTD banks and small banks in the fixed effect estimations. Based on the estimation of the fixed effect model, the results show a positive and significant correlation between bank size and loan sale, consistent with the suggestion (Minton et al. 2004; Martin-Oliver and Saurina, 2007) that relatively large banks are more likely to be involved in the OTD model of lending. Moreover, our results suggest that high-OTD banks holding larger amount of illiquid C&I loans tend to be engaged in OTD lending. However, these findings are not significant in the SGMM estimation.

Table 5.7: Fixed effect estimations for the motivations of using OTD lending during the pre-crisis and crisis period

Fixed effects regressions of changes of loan sale on mortgage origination, non-performing loans, cost of funding and bank characteristics during pre-crisis and after-crisis period. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. C&I ratio is computed as commercial and industry loans divided by total assets. All standard errors, clustered at the bank level, are reported in parentheses. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Pre-crisis	(2) Pre-crisis excluding large banks	(3) After crisis	(4) After crisis excluding large banks
Origination	0.668***	0.670***	0.570***	0.553***
	(6.75)	(6.61)	(10.46)	(10.43)
Non-performing loan	-2.944	-2.872	2.020***	2.106***
	(-1.61)	(-1.56)	(2.99)	(3.01)
Cost of funding	-2.130	-0.944	6.278***	7.191***
	(-0.30)	(-0.13)	(5.93)	(6.82)
LogTA	0.160	-0.017	0.157	0.280***
	(0.44)	(-0.05)	(1.18)	(2.64)
Capital ratio	-6.155**	-5.332*	-0.466	-0.332
	(-2.19)	(-1.90)	(-0.53)	(-0.38)
Deposit ratio	-0.031	0.054	0.716	0.679
	(-0.03)	(0.05)	(1.07)	(0.99)
Liquid ratio	1.226	1.411	-0.780**	-0.839**
	(1.43)	(1.64)	(-2.34)	(-2.51)
C&I loans	1.888	2.581*	-0.423	-0.232
	(1.25)	(1.74)	(-0.61)	(-0.33)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Cons	-1.272	1.361	-2.128	-3.844**
	(-0.24)	(0.28)	(-1.09)	(-2.45)
Observations	1430	1357	4750	4484
R^2	0.106	0.116	0.256	0.269

We then divide the whole sample period into two periods, before crisis, from 2006Q3 to 2007Q2, and after crisis, from 2007Q3 to 2009Q2, to examine the determinants of using OTD model across the business cycle. The estimation results are shown in the Table 5.7. Consistent with our previous finding, banks originating more OTD loans tend to be highly engaged in the OTD model after the financial crisis, as reported via Model 3. This relationship remains significant after we exclude banks with total assets more than $1 billion. The results reported in Models 1 and 2 reveal that the quality of mortgage loans does not have a significant effect on selling originated OTD loans before the financial crisis. One possible explanation is that investors may believe that mortgage loans will not default due to credit enhancements given by Government Sponsored Enterprises and they can also refinance mortgage loans due to increasing house prices. Therefore, blooming housing conditions undermine the effects of loan default on selling mortgage loans. The coefficient of non-performing loans is positively significant in Models 3 and 4, which confirms our previous findings that banks with larger amounts of lower quality of mortgage loans seem to be active in selling loans since large amounts of mortgage loans suffer default after the third quarter of 2007. This is also consistent with banks tending to sell low default risk loans during housing bloom period and selling loans with high default risk after the crisis (Agarwal et al., 2012).

Supporting the capital arbitrage hypothesis, our results indicate that banks are more likely to use the OTD model to alleviate capital requirements when they face capital constraints before the crisis as the coefficient of capital ratio is significantly negative in Models 1 and 2. As expected, we find that loan sale is positively affect by cost of funding during the after-crisis period in Models 3 and 4, which confirms the proposition that that banks can use OTD lending when they face severe funding constraints during the financial crisis. Not surprisingly, this coefficient is not significant due to a blooming house market and very liquid financial market conditions before 2007Q2, with the results reported via Model 1 and Model 2. Moreover, there is a negative and significant coefficient on the liquid ratio term, which indicates that banks' involvement in the OTD model can alleviate liquidity shortage during the financial downturn. Therefore, banks mainly use the OTD to raise funding to alleviate funding and liquidity shortages due to illiquid market conditions during the crisis.

5.7 Conclusion

The aim of this thesis is to explore the motivation for use of the OTD model in US commercial banks. We extend the period until 2009Q2 and record a contraction in OTD activities, especially including the period in which banks faced severe funding shortage. Our results confirm that banks with more OTD mortgage loans tend to sell those loans from their balance sheets. Banks with riskier mortgage loans portfolios will also be engaged in the OTD model. In addition, high-OTD banks and small banks resort to the OTD model to when they face higher cost of funding and liquidity constraints. Besides that, arbitrage capital is more important for small banks since they seem to be capital-constrained. We also examine whether the OTD model can be used during the financial crisis, especially during the most severe market conditions in 2008Q4. Our results suggest that the OTD model could be used during this period. That could be explained by the fact that Federal Reserve Banks sought to take actions to preserve sufficient liquidity in OTD markets during the financial turmoil.

A new regulatory framework has been developed to re-build a sustainable OTD framework during post-crisis period. Our results support adequate risk retention proposed in the Dodd-Frank Act as banks with riskier mortgage portfolios tend to increase loan sale, especially lower quality loans. In order to mitigate banks to sell bad loans, banks also are required to disclosure more information about loans that are sold to other parties, increasing the transparency of OTD activities. Besides that, banks also need to reduce their incentives to lend to riskier borrowers, reducing incentives to sell riskier loans to securitization pools in order to rebuild a sustainable OTD framework.

Chapter 6

The OTD Model of Lending and Bank Credit Supply

6.1 Introduction

The originate-to-distribute model (OTD model) allows banks to sell off loans from their balance sheets to third parties rather than holding them until maturity. This has reduced the importance of one fundamental function of banks in liquidity transformation (Diamond and Dybvig 1983). In the traditional bank lending model, banks mainly use deposits to finance loans. The OTD model allows banks to transfer illiquid loans to marketable securities. After banks sell off loans from their balance sheets, they can rise new funding to finance loans and cover liquidity needs, making them be less dependent on the traditional source of funding.

There is a growing literature that OTD model has had a positive impact on credit supply. Cebenoyan and Strahan (2004) suggest that loan sales lead to an increase in credit supply associated with increased bank leverage and profitability. Banks tend to lower lending standards and lend to more risky borrowers after they sell off loans, leading to an increase in aggregate credit supply (Dell' Ariccia and Marquez, 2006; Demyanyk and Hemert, 2009). Mian and Sufi (2008) demonstrate evidence of credit expansion in high latent demand zip codes driven by OTD activities. Loutskina and Strahan (2009) argue that the OTD model enables banks to obtain balance sheet liquidity and increases their willingness to provide more credit, through examining loan-level data of US market from 1992 to 2004. Dell' Ariccia et al. (2010) provide evidence of high credit growth in US driven by OTD activity, especially in the areas with lower denial rates. Loutskina (2011) find that OTD model enables banks to make more loans to the economy by using a sample of US commercial banks from 1976 to 2007. For European banks, Altunbas et al. (2009) suggest that banks are highly involved in OTD market are more likely to increase the supply of credit during the period between 1999 and 2005. This chapter aims to address some open questions. Does OTD lending lead to a positive effect on bank credit supply since it can be used to finance loans and liquidity? Does the impact of OTD lending on credit supply vary across bank with different intensities of involvements in the OTD model of lending and across bank size? Can OTD lending be used during the financial crisis? Does the OTD lending have changed the effect of changes of monetary policy on loan supply? Addressing these issues has two main implications for policy makers. First, it gives a comprehensive assessment the impact of OTD lending on the loan supply to give some hints to regulators to develop the regulations for re-establishing a sustainable OTD framework. Second, it allows bank regulatory authorities to understand the mechanisms of bank lending channel of monetary policy transmission in the context of OTD business model.

Based on our previous study, we know that banks resort to OTD model as it can provide liquidity and a source of funding. In this section, we extend our research to examine further whether the OTD model has an influence on credit supply as liquidity and funding provider vary across different levels of involvement in the OTD business model and across bank size. We first divide our sample into two subsamples, low-OTD banks and high OTD banks based on the average value of origination to resell to total mortgage loans and examine whether the OTD lending has a significant impact on bank credit supply from 2006Q3 to 2009Q2. Our results show that there is a disparity effect of OTD activities on bank lending between low- and high-OTD banks. We find a significant correlation between the OTD lending and credit supply in the high-OTD banks but the relationship is not significant for low-OTD banks. This is consistent with the literature that the OTD model has played a very important role in an increase in the supply of credit (Demyanyk and Hemert, 2009; Mian and Sufi, 2009; Dell'Ariccia et al., 2012). We then divide banks into two groups, small banks and large banks based on the value of total assets. Our results suggest that OTD lending appears to be positive related to loan supply in both small and large banks. Moreover, our previous study shows that OTD lending could be used to offload loans from balance sheets during the financial crisis, so we want to examine whether banks can still use OTD lending to obtain liquidity, leading to an increase in credit supply during that period. Our results indicate that the there is no significant relationship between OTD lending and the supply of loans during the financial crisis. This may be because banks hoard liquidity rather than supplying credit to the economy after they obtain liquidity through selling loans in the context of illiquid market conditions. Finally, our research is closely linked to Altunbas et al. (2009), Gambacorta and Marques-Ibanez (2011), Loutskina (2011) suggest that the OTD model reduces the effectiveness of monetary policy. We extend their work and examine the relationship between OTD model and bank lending channel following monetary policy changes. We observe positive effects of the impacts of OTD lending in high-OTD banks and small banks. This effect is pronounced in high-OTD banks and small banks because they are highly involved in the OTD model of lending.

There are three main contributions in our study. First, it gives a better understanding of the impact of OTD lending on credit supply. There are few papers that assess the impact of OTD lending on credit supply across different levels of involvement in the OTD model of lending at the frontend of securitization. Second, we also examine this impact varies across bank size and across business cycle. Our research contributes to existing literature (Dell' Ariccia et al., 2012, Demyanyk and Hemert, 2009, Mian and Sufi, 2009) that the OTD lending plays a positive role on credit supply. We extend this literature and suggest that this positive effect is not significant during crisis period. Moreover, our results are in line with (Altunbas et al., 2009; Gambacorta and Marques-Ibanez, 2011; Loutskina, 2011) and provide evidence that the OTD lending model has changed the link between changes of monetary policy on loan supply. Second, our research focuses on one asset class, 1-4 family residential mortgage loans, which account for the majority of OTD lending. Furthermore, we examine this effect at the frontend of securitization channel at originating bank level whereas other existing studies investigate the impact of OTD activities on credit supply during the process of securitization.

The rest of the chapter is organized as follows. In section 6.2, Model specification is In Section 6.3, some empirical results and discussion are shown in Section 5.3. Section 6.4 concludes the paper.

6.2 Model Specification

Based on our research in the previous chapter, we know that banks resort to OTD model as it can raise funding and provide liquidity and they can use that funding to finance more loans. In this section, we extend our research to examine whether the OTD model has a positive impact on credit supply as liquidity and funding provider vary across different levels of involvement in the OTD business model and across bank size. Given the previous result that banks employ the OTD model to finance loans and liquidity needs, they are more likely to have a significant supply of credit. To test this hypothesis, we regress quarterly change of the logarithm of loan growth on the indicator of OTD activities and some variables and bank characteristics which may affect the loan growth, based on the previous literature. We use both FE Model and SGMM to estimate the regressions. The Models for both methods are shown respectively in the Section 6.2.1 and Section 6.2.2.

6.2.1 Fixed Effect Estimation

$$\Delta ln(loan)_t = \alpha_1 + \beta_1 Origination_{it} + \beta_2 NPL_{it-1} + \beta_3 \Delta ir_t +$$

$$\sum_{j=1}^{5} \gamma_j \, X_{jt-1} + \sum_{k=1}^{2} \varphi_k \, \Delta M_{kt} + \varepsilon_{1t}$$

Credit supply is measured as the difference in natural logarithm of gross loan $\Delta ln(loan)_t$. Gross loan is the total amount of credits that a bank provides during the quarter. Origination is the ratio of mortgage loans origination for resale to the beginning of period total mortgage loans. NPL is measured by non performing mortgage loans of 1-4 family residential mortgage loans divided by total mortgage loans. Cost of funding is the ratio of interest expense to total liabilities. X_{jt-1} is denoted by a set of control variables, such as total assets, deposits, capitals, liquid assets. Total asset is the natural logarithm of total assets at the beginning of a quarter. Loan ratio is the share of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as liquid assets as the fraction of total assets. We also add a BHC dummy variable that equals to one if the bank is part of a single-bank holding company, equals to two if it is affiliated with a multi-bank holding company, and zero otherwise (Ashcraft, 2008). In addition, Bernanke and Blinder (1992) use Fed fund rate as a proxy measure of changes of monetary policy and suggest that tightening monetary policy seems to reduce the willingness for banks to supply credit. Quarterly change in Fed fund rate Δir_t need to be included to measure the changes of monetary policy. We also include quarterly changes in macroeconomic variables ΔM_{kt} to account for demand of bank loans.

6.2.2 System GMM Estimation

$$\Delta ln(loan)_t = \alpha_1 + \beta_4 Origination_{it} + \beta_5 NPL_{it-1} + \beta_6 \Delta ir_t + \sum_{j=1}^{5} \delta_j X_{jt-1} + \sum_{k=1}^{2} \theta_k \Delta M_{kt} + \mu \Delta ln(loan)_{t-1} + \varepsilon_{2t}$$

The fixed effect model is biased in the dynamic model because the fixed effect is correlated with the lagged dependent variables (LDV). Therefore, SGMM estimation technique is applied here. In order to control for endogneity issues which arise from previous loan growth affect the current supply of bank loans, we add a lagged value of loan growth in the model. Fed fund rate, market variables and BHC dummy are considered as exogenous variables whereas the rest are taken as predetermined variables.

6.3 Empirical Results

Our results show that the OTD lending has a disproportionate effect on credit supply across banks with different levels of engagement in the model. We find that there is a positive and significant relationship between Origination and loan growth for high-OTD banks in both FE and SGMM estimations as the coefficients reported in Table 6.1 and Table 6.2 respectively. This remains significant after we exclude banks with total assets more than $10 billion with coefficient estimated of 0.017 in Model 4. Consistent with our previous research, these findings confirm that the OTD business model can contribute to a significant increase in credit supply for high-OTD banks since OTD lending provides an additional source of funding to finance loans and liquidity. However, the impact on credit supply is insignificant for low OTD banks. Moreover, we then divide banks into small and large banks and also find a significant loan supply which is driven by OTD lending for two kinds of banks in both FE and SGMM estimations. Thus, our findings are consistent with (Loutskina, 2011; Mian and Sufi, 2009; Demyanyk and Hemert, 2009 and Dell' Ariccia et al., 2012) who suggest that the OTD model leads to an expansion of credit supply.

Furthermore, we observe a significantly negative relationship between bank loan performance and loan growth in the SGMM estimations, which suggests that banks tend to loosen their lending standards and lend to more risky borrowers, leading to an increase in credit supply (Demyanyk and Hemert, 2006; Dell' Ariccia et al., 2010). However, we cannot find a significant relationship for high-OTD and large banks in the FE estimations. As we expect, banks with higher return are likely to increase credit supply as indicated by a positive relationship between banks return and credit supply in both FE and SGMM estimations.

Table 6.1 Fixed effect estimations for effects of OTD lending on credit supply

We show fixed effects regressions of changes of loan growth on mortgage origination, non-performing loans, cost of funding and bank characteristics from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Fed fund rate measures the changes of monetary policy. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. All standard errors, clustered at the bank level, are reported in parentheses. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) high-OTD banks	(3) Small banks	(4) Large banks
OTD loans	0.004	0.036***	0.023***	0.059***
	(0.61)	(5.26)	(3.41)	(3.28)
Non-performing loans	-0.108	-0.261***	-0.143	-0.310**
	(-1.50)	(-2.59)	(-1.58)	(-2.26)
Fed fund rate	0.002	0.005	0.003	0.013***
	(1.07)	(1.38)	(1.02)	(3.17)
LogTA	-0.117***	-0.206***	-0.188***	-0.287***
	(-6.44)	(-7.68)	(-5.68)	(-5.73)
ROA	0.928***	2.161***	0.824***	1.770***
	(5.79)	(5.13)	(3.08)	(4.75)
Capital ratio	0.289**	0.215	0.528***	0.190
	(2.51)	(1.10)	(2.64)	(0.76)
Deposit ratio	-0.074	-0.171**	-0.063	-0.205***
	(-1.47)	(-2.43)	(-1.10)	(-2.77)
Liquid ratio	0.082**	0.092*	0.075	0.165***
	(2.45)	(1.68)	(1.33)	(3.70)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
cons	1.570***	2.954***	2.312***	4.300***
	(6.13)	(7.63)	(5.33)	(5.64)
Observations	3629	4002	3147	4484
R^2	0.163	0.164	0.160	0.238

Table 6.2 SGMM estimations for effects of OTD lending on credit supply for low- and high-OTD banks

This table reports the estimates of changes of loan growth on mortgage origination, non-performing loans, cost of funding and bank characteristics from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Fed fund rate measures the changes of monetary policy. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. The model is estimated by system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) Low-OTD banks excluding large banks	(3) high-OTD banks	(4) high-OTD banks excluding large banks
Origination	-0.004	0.006	0.022***	0.017***
	(-0.36)	(0.63)	(3.86)	(2.99)
Non-performing loans	-0.411***	-0.258**	-0.551***	-0.418**
	(-2.75)	(-2.32)	(-3.51)	(-2.17)
Fed fund rate	-0.005**	-0.007***	-0.011***	-0.013***
	(-2.16)	(-3.38)	(-4.73)	(-4.92)
LogTA	-0.026***	-0.021**	-0.001	-0.006
	(-2.84)	(-1.97)	(-0.17)	(-0.63)
ROA	0.806***	0.538***	0.852***	0.607***
	(3.56)	(2.62)	(4.62)	(2.78)
Capital ratio	-0.077	0.294	0.747***	0.683**
	(-0.33)	(1.31)	(2.81)	(2.41)
Deposit ratio	0.087	-0.051	0.072	0.088
	(0.84)	(-0.56)	(0.56)	(0.66)
Liquid ratio	-0.055	-0.112*	0.016	-0.075
	(-0.74)	(-1.90)	(0.25)	(-1.05)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
cons	0.400***	0.276*	-0.071	0.010
	(2.92)	(1.72)	(-0.73)	(0.07)
Observations	3429	3243	3755	3233
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.715	0.163	0.485	0.426
Hansen test(p-value)	0.409	0.407	0.389	0.345

Table 6.3 SGMM estimations for effects of OTD model of lending on credit supply for small and large banks

This table reports the estimates of changes of loan growth on mortgage origination, non-performing loans, cost of funding and bank characteristics from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Fed fund rate measures the changes of monetary policy. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. The model is estimated by system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Small banks	(2) Large banks
OTD loans	0.014***	0.010***
	(4.62)	(2.85)
Non-performing loans	-0.284***	-0.162**
	(-3.91)	(-2.26)
fed fund rate	-0.007***	-0.010***
	(-3.49)	(-6.03)
LogTA	-0.001	-0.004**
	(-0.11)	(-2.05)
ROA	0.565***	1.199***
	(2.65)	(7.24)
Capital ratio	0.164	-0.038
	(1.30)	(-0.31)
Deposit ratio	-0.034	-0.130
	(-0.54)	(-1.42)
Liquid ratio	-0.001	0.012
	(-0.02)	(0.31)
BHC flag	Yes	Yes
Market controls included	Yes	Yes
Lagged dependent variables included	Yes	Yes
cons	-0.002	0.075**
	(-0.03)	(2.14)
Observations	2939	4127
Wald test (p-value)	0.000	0.000
MA(1) (p-value)	0.000	0.000
MA(2) (p-value)	0.351	0.110
Hansen test (p-value)	0.252	0.421

Our results show that bank characteristics contribute to an increase in the supply of loans. Not surprisingly, we observe a positive correlation between capital and credit supply based on SGMM estimations of Models 3 and 4, which suggests that high-OTD banks with more capital tend to increase the supply of credit since they have more resources to finance loans. We also document similar findings in low-OTD and small banks based on the estimations from Fixed Effects model. In addition, we find that banks with less deposits appear to increase credit supply, as indicated by the negative relationship between deposit ratio and loan growth, which confirms that the OTD model makes banks less dependent on the traditional source of funding (Loutskina, 2011). However, this finding is significant in FE Model but insignificant in the SGMM Model.

We want to examine further whether OTD model still can be used to supply credit during the financial turmoil vary across banks with different intensities of involvements in the OTD model and vary across bank size. In order to conduct our tests, we add a dummy variable *After* which is equal to one after 2007Q3 and zero otherwise, and use

Origination interacted with *After* dummy to isolate the impact from Pre-crisis period.[21] The modified model is as follows:

$$\Delta \ln(loan)_i = \alpha_i + \beta_7 Origination_{it} + \beta_8 Origination_{it} * After$$

$$+\beta_9 NPL_{it-1} + \beta_{10}\Delta ir_t + \sum_{j=1}^{5} \vartheta_j X_{jt-1} + \sum_{h=1}^{2} \rho_h \Delta M_{kt}$$

$$+\mu_1 \Delta \ln(loan)_{it-1} + \beta_{11} After + \varepsilon_{3t}$$

The estimation results are shown in the Table 6.4. We cannot find a significant relationship on the interaction items in all four regressions, which indicates that OTD lending cannot contribute to a significant loan growth during after-crisis period. Based on our previous study, we know that OTD model of lending can be used in the financial downturns as the results are reported in the Table 5.3. However, we cannot find a significant loan growth driven by OTD lending after the financial crisis. This could confirm that banks tend to hoard liquidity and are not willing to make loans due to concerns of liquidity shortage during financial crisis (Cornett, 2011). Banks appear to hold more liquid assets rather than lend them out because unconventional monetary policy is ineffective when it is not beyond a certain point. In this case, banks need

[21] Since the Federal Reserve Board (2010) suggests that the residential mortgages market tightened considerably over most of the period 2007:Q3–2009:Q2

to hold on additional liquidity created by the Federal Reserve to increase lending (Benmelech and Bergeman, 2012).[22] The other possible explanation for hold liquidity is that banks would like to maximise their profits by acquiring assets at fire-sale prices (Acharya et al., 2011).

Loutskina and Strahan (2006) provide evidence that securitization reduces the effectiveness of the impact of changes of monetary policy on the bank lending channel in the US jumbo mortgage market. Loutskina (2011) suggests that the OTD lending model provides an additional source of funding, making banks less sensitive to cost of funding shocks. Then we want to investigate how credit supply is affected by OTD activities following the changes of monetary policy. To conduct our research, an interaction $\Delta ir_t * Orignation$ is added in the model to measure the effect of OTD lending and we expect the coefficient on this interaction term to be significantly positive. The modified model is estimated as follows:

$$\Delta ln(loan)_t = \alpha_1 + +\beta_{12} Origination_{it} + \beta_{13} NPL_{it-1} + \beta_{14} \Delta ir_t + \sum_{j=1}^{5} \omega_j X_{jt-1} + \sum_{k=1}^{2} \sigma_k \Delta M_{kt} + \mu_2 \Delta ln(loan)_{t-1} + \beta_{15} \Delta ir_t * Orignation + \varepsilon_{4t}$$

[22] They use "credit traps" to describe this scenario that the central bank makes efforts to stimulate lending, but liquidity still remain trapped in banks.

Table 6.4: Effects of OTD lending on credit supply with crisis dummies

This table reports the estimates of changes of loan growth on mortgage origination, non-performing loans, cost of funding and bank characteristics from 2006Q3 to 2009Q2. Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Cost of funding is the ratio of interest expense to total liabilities. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. C&I ratio is computed as commercial and industry loans divided by total assets. The model is estimated by system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level.

	(1) Low-OTD banks	(2) high-OTD banks	(3) Small banks	(4) Large banks
Origination	-0.007	0.023***	0.009***	0.017**
	(-0.44)	(3.85)	(2.63)	(2.37)
Origination*After	0.020	0.003	0.003	-0.010
	(1.18)	(0.64)	(0.88)	(-1.29)
Non performiming loans	-0.345**	-0.492***	-0.277***	-0.152*
	(-2.32)	(-3.04)	(-3.83)	(-1.96)
Fed fund rate	-0.003	-0.010***	-0.005**	-0.008***
	(-1.38)	(-4.27)	(-2.09)	(-4.13)
LogTA	-0.034***	-0.001	-0.003	-0.004**
	(-2.89)	(-0.12)	(-0.62)	(-2.03)
ROA	1.056***	0.923***	0.592***	1.294***
	(3.95)	(4.84)	(2.73)	(7.17)
Capital ratio	-0.168	0.742***	0.140	-0.025
	(-0.72)	(2.75)	(1.16)	(-0.20)
Deposit ratio	0.148	0.060	-0.061	-0.177*
	(1.17)	(0.44)	(-0.95)	(-1.86)
Liquid ratio	-0.095	0.017	0.007	0.012
	(-1.48)	(0.24)	(0.18)	(0.32)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
Time dummy included	Yes	Yes	Yes	Yes
cons	0.523***	-0.073	0.046	0.076**
	(2.98)	(-0.78)	(0.60)	(2.16)
Observations	3429	3755	2939	4127
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.769	0.630	0.346	0.124
Hansen test(p-value)	0.316	0.396	0.551	0.355

Table 6.5: Effects of OTD lending on credit supply with an interaction term with monetary policy indicator

Origination is mortgage loans origination for resell divided by the beginning of period total mortgage loans. NPL measures mortgage loan losses of the bank divided by its beginning of quarter total mortgage loans. Total assets ratio is the log value of beginning of quarter total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets. Deposit is the ratio of total demand deposit to total assets. Liquid assets ratio is defined as the ratio liquid assets to total assets. C&I ratio is computed as commercial and industry loans divided by total assets. The model is estimated by system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first–difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) high-OTD banks	(3) Small banks	(4) Large banks
Origination	-0.004	0.008***	0.011***	0.033***
	(-0.36)	(3.01)	(3.40)	(3.29)
Non-performing loans	-0.415***	-0.239***	-0.286***	-0.575***
	(-2.75)	(-2.69)	(-2.99)	(-3.89)
fed fund rate	-0.005*	-0.012***	-0.010***	-0.008***
	(-1.79)	(-5.55)	(-4.21)	(-3.53)
LogTA	-0.026***	-0.001	0.001	-0.008**
	(-2.86)	(-0.72)	(0.12)	(-2.12)
ROA	0.811***	0.725***	0.540**	0.971***
	(3.60)	(3.35)	(2.13)	(5.20)
Capital ratio	-0.081	0.109	0.015	0.097
	(-0.34)	(0.92)	(0.15)	(0.40)
Deposit ratio	0.090	0.073	0.040	0.011
	(0.86)	(1.03)	(0.68)	(0.11)
Liquid ratio	-0.056	-0.056	-0.058	-0.005
	(-0.76)	(-1.40)	(-1.40)	(-0.09)
Origination*Fed fund rate	-0.002	0.005*	0.006*	-0.000
	(-0.21)	(1.90)	(1.72)	(-0.21)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables incl	Yes	Yes	Yes	Yes
cons	0.401***	0.012	0.004	0.121*
	(2.93)	(0.41)	(0.06)	(1.74)
Observations	3429	3755	2939	4127
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.720	0.083	0.118	0.538
Hansen test(p-value)	0.46	0.361	0.648	0.492

From Table 6.5, we document a negative relationship between Fed fund rate and loan supply as the coefficients of Fed fund rate are significant and negative reported in all regressions. As expected, the coefficients of interaction terms are significant and positive as shown in Models 2 and 3, which indicates that the positive effects of OTD activities on bank lending, especially for high-OTD banks and small banks. The reason that positive effects mainly exist in the high-OTD banks and small banks can be explained by their being highly involved in the OTD model of lending. Our results are in line with previous literature (Altunbas et al., 2009; Gambacorta and Marques-Ibanez, 2011; Loutskina, 2011) that OTD lending tends to change the effect of changes of monetary policy on the bank lending channel.

6.4 Conclusion

This chapter investigates the impact of OTD lending on credit supply in US commercial banks. Our study gives a comprehensive assessment of this effect by examining it in low- and high-OTD banks. Our results show that a disparity in effects between those two groups. The effect is significant in high-OTD banks but not in low-OTD banks. This could complement study earlier studies (Dell' Ariccia et al., 2012, Demyanyk and Hemert, 2009, Mian and Sufi, 2009) who suggest that the OTD business model can expand the supply of credit to the real economy.

Furthermore, OTD lending cannot contribute to a significant supply of loans during the financial turmoil, but banks tend to use the model to obtain liquidity. That could explain why Federal Reserve Banks sought to take actions to preserve sufficient liquidity in the OTD market during the financial crisis.

Our study also suggests that the OTD model has changed the transmission mechanism of monetary policy on bank lending channel since we observe positive effects of the changes of monetary policy on loan supply. Regulators have to take into account the effect that securitization increases the supply of credits when they carry out tightening monetary policy during a lending boom, especially focussing on banks that are highly engaged in the OTD market (high-OTD banks and small banks). In addition, regulators can consider OTD lending as a tool to enhance policy effect and increase liquidity of financial system in the financial recessions. However, our study is limited to OTD lending of 1-4 family mortgage loans and does consider other forms of assets classes. Moreover, our study does not take the impact of other forms of credit provided to the economy into account. Therefore, our conclusions cannot fully understand the impact of OTD lending on transmission mechanism of monetary policy through bank lending channel.

The Basel III framework has been proposed to reduce banks' risk-taking behaviour by increasing capital, liquidity and leverage requirements after the financial crisis. Meanwhile, it prevents banks from making the use of the OTD model of lending, leading to a decrease in credit supply (Bank for International Settlements, 2011). Our findings suggest that it is not an optimal solution for regulators to stabilize banking system by excessively downsizing the OTD model of lending at expense of supply of credit to the economy.

Chapter 7

The Impact of OTD Lending on Bank Risk Taking Behaviour

7.1 Introduction

Over the last three decades, loan sale and securitization have changed the traditional business framework from "originate-to-hold" into "originate-to-distribute" (OTD) and allowed banks convert illiquid assets into marketable securities. Banks have obtained many benefits from their involvement in the OTD market. A bank may lower its cost of capital (Pennacchi, 1988), improve risk management and increase profitability (Cebenoyan and Strahan, 2004 and Jiangli and Pritsker, 2008). Since the OTD model can provide an additional source of funding, it reduces the sensitivity of banks to adverse financial shocks (Loutskina and Strahan, 2006; Loutskina, 2011). However, a concern has been raised that the OTD model also increases bank risk taking and even systemic risk of the whole banking system as securitized products created under the OTD model suffered high default rate from 2007. Brunnermeier (2009) suggests that the heavy reliance on wholesale funding of banks involved in the OTD model contributed to the financial crisis.

Much research has been done to examine the impact of the OTD model on banks' risk taking behaviour. Previous studies suggest that the OTD model can allow banks to reduce expected regulatory costs (Pennacchi, 1988) by conserving costly capital or bankruptcy costs (Gorton and Souleles, 2006). These papers suggest that the model reduces bank risk. Alternatively, it may increase bank risk if banks hold resource for loans they sell (Pennacchi, 1988). Some studies investigate this effect by examining whether the OTD model allows banks to transfer credit risk from their balance sheets. Since the OTD model has changed banks' role fundamentally from the traditional lending relationship to one of origination and distribution of loans, this change may affect the banks' incentives to take on new risks. It is suggested that banks usually sell their safer loans and retain more risky loans (Greenbaum and Thakor, 1987; Benveniste and Berger, 1987), which indicates that banks tend to take on more risk. Bad loans may be retained on the banks' balance sheets SPVs sponsored by them without being transferred to investors, so retaining the credit risk exposure (Shin, 2009). From the perspective of individual banks, the OTD model can be used to modify the risk profile because it enables banks to manage their loan portfolios' credit risk more effectively, but it could increase banks' exposure to risk by lending more to riskier borrowers (Cebenoyan and Strahan, 2004). When credit has been filled for prime borrowers, banks are more like to lower their lending standards and lend to riskier borrowers (Dell'Ariccia and Marquez, 2006; Dell' Ariccia et al., 2010), resulting in a deterioration of loan portfolios. A higher default rate is also driven by excessive credit supply in high latent demand zip (Mian and Sufi, 2009).

The OTD model may increase bank risk because banks have less incentive to monitoring borrowers' behavior after loans are sold. In traditional bank lending model, banks have an obligation to delegate monitoring borrowers after they make loans (Diamond, 1984). Since the OTD lending enable banks to offload loans, it also lowers monitoring and screening incentives for banks on the loans. Recent studies provide both theoretical and empirical evidence that banks have reduced monitoring incentives after selling loans, resulting in higher default rates of securitized loans (Parlour and Plantin, 2008; Bubb and Kaufman, 2009; Keys et al., 2010; Purnanandam, 2011;). Keys at al. (2010) use the loan-level from Loan Performance ABS data to find that the default rates of securitized loans with FICO score above 620 are higher than those with lower scores in the low documentation subprime market. Purnanandam (2011) also finds that banks which are highly active in OTD model has associated with higher default rates since they have lower monitoring incentives on borrowers after they have moved mortgage loans off their balance sheets.

Finally, the OTD model may increase bank risk if banks engage in the OTD model and sell loans to reduce capital requirements. Meanwhile, banks providing implicit resource with SPVs buy back non-performing loans, so they are exposure to credit risk with reduced regulatory capital when they buy back those default loans, leading to an increase in the bank insolvency risk. Taking this into account, Jiangli and Pritsker (2008) examine the impact of mortgage securitization on insolvency risk by using US Bank Holding Company data from 2001 to 2007. They find that the OTD model plays a positive role in bank risk management, leading to a decrease in insolvency risk. Casu et al. (2011), also using bank holding company data from 2001 to 2007, suggest a negative relationship between securitization and bank risk-taking that banks with larger amounts of outstanding securitized loans are more likely to choose loan portfolios with lower credit risk. More importantly, this negative relationship mainly is associated with securitization of mortgages and home equity lines of credit.

Thus, the net impact of the OTD model of lending on risk-taking behaviour of banks is ambiguous and needs to be tested. Our research aims at understanding the impact of participation in the OTD model of lending on bank risk taking. Specifically, we use bank-level data to examine whether intensive engagement in the OTD market has a detrimental effect on bank stability from 2006Q3 to 2009Q2. We first investigate whether the OTD model leads to an increase in bank risk taking based on banks' involvements in the OTD model and bank size. We divide our banks into two groups, low- and high-OTD banks, based on the average value of origination ratio across all quarters and we use three risk characteristics of banks to measure bank risk taking behaviour: (i) non-performing loans; (ii) net charge-offs and (iii) z-Score. Our results indicate that the OTD model has adverse effect on bank riskiness for two groups, increasing default rate and net charge-offs. We also find that the OTD model increases bank instability and possibilities to default as indicated by lower level of z-Score. We also divide banks into small banks and large banks and investigate the impact of OTD model on bank risk-taking across bank size. Our results show that small banks are much riskier than large banks since they are relative highly involved in the OTD lending. In order to further investigate the driving forces of bank risk-taking, we decompose the z-Score into portfolio risk and leverage risk, the results indicates that the OTD lending mainly leads to an increase in portfolio risk but not in leverage risk.

Our research has twofold contributions to the existing literature. First, we examine the impact of the OTD model on bank risk at the frontend of securitization whereas previous research focuses on the process of securitization. Moreover, few papers investigate the relationship between the OTD model of lending and bank risk-taking behaviour based banks' involvement in the OTD model and bank size. This study contributes to the existing literature (Cebenoyan and Stranham, 2004; Dell'Ariccia and Marquez, 2006; Purnanandam, 2011) finding that bank riskiness is positively related to OTD lending. Finally, our study records a research period of contraction in the OTD lending during financial crisis and provides empirical evidence that banks are heavily dependent on wholesale funding participating via the OTD model of lending during the pre-crisis period, increasing bank risk-taking and contributing to the current financial crisis (see also Brunnermeier, 2009).

Second, our research has important implications for regulators. Our results show that small banks involved in the OTD market are more likely to suffer default and become distressed, suggesting that regulators should pay more attention to small banks which are involved in the OTD model of lending. Furthermore, since we find that the OTD model of lending has a disparate effect on the bank risk taking between small banks and large banks, this suggests that regulators need to treat the two groups differently to avoid 'one size fits all' in bank regulation, re-establishing a sustainable OTD framework.

The rest of the chapter is organized as follows. Section 7.2 reports some descriptive statistics of some variable used in our study. In section 7.3. We describe empirical specification and then some empirical results are shown in Section 7.4. Section 7.5 concludes the chapter.

7.2 Descriptive Statistics

Table 7.1 reports average originated OTD loan ratio and bank risk characteristics measured in three different ways based on banks' involvements in OTD lending and bank size in each quarter. It can be clearly seen that the average percentage of OTD banks highly engaged in the OTD model are much larger than those with lower involvement (14% for low-OTD banks vs 48% for high-OTD banks in 2006Q3 and 20% for low-OTD banks vs 70% for high-OTD banks in 2009Q2). We also see a steady increase in the average value of originated OTD loans to total mortgage loans until 2007Q2. From 2007Q3, OTD lending experiences a sharp decrease until 2008Q4, then starts to increase after the peak of the financial crisis. A similar trend is found for small and large banks. The table contains information about three different risk measures across bank with different levels of involvement in the OTD model and across bank size over all quarters. We find that the quarterly average of non-performing ratio and net charge-off ratio of high-OTD banks are slightly higher than that of low-OTD banks. However, the average z-Score of high-OTD banks is slightly lower relative to that of low-OTD banks. This is consistent with banks with highly involvement in the OTD model having higher risk exposure (Purnanandum, 2011).

Table 7.1: Summary statistics

Quarter	Average OTD loans		NPLs ratio		Net charge-offs		Z-score	
	Low	High	Low	High	Low	High	Low	High
2006Q3	0.147	0.476	0.616	0.659	0.038	0.051	29.866	30.102
2006Q4	0.132	0.456	0.692	0.670	0.071	0.092	34.158	33.046
2007Q1	0.109	0.426	0.785	0.791	0.022	0.029	32.418	32.170
2007Q2	0.124	0.477	0.884	0.866	0.043	0.065	32.024	31.559
2007Q3	0.118	0.381	0.991	1.044	0.069	0.099	32.245	30.352
2007Q4	0.102	0.370	1.147	1.276	0.136	0.164	38.302	39.066
2008Q1	0.105	0.432	1.383	1.534	0.062	0.079	36.536	35.535
2008Q2	0.098	0.436	1.564	1.796	0.132	0.171	33.868	33.396
2008Q3	0.071	0.365	1.807	2.092	0.220	0.272	31.656	32.531
2008Q4	0.069	0.354	2.223	2.451	0.364	0.409	44.125	42.035
2009Q1	0.150	0.678	2.689	3.013	0.117	0.182	37.186	34.250
2009Q2	0.202	0.702	3.105	3.410	0.308	0.378	33.357	32.194
	Small	Large	Small	Large	Small	Large	Small	Large
2006Q3	0.613	0.133	0.666	0.603	0.042	0.047	29.982	29.986
2006Q4	0.563	0.156	0.702	0.657	0.078	0.085	34.661	32.427
2007Q1	0.456	0.142	0.844	0.728	0.024	0.028	33.306	31.218
2007Q2	0.487	0.171	0.927	0.822	0.054	0.054	32.894	30.669
2007Q3	0.402	0.140	1.129	0.907	0.083	0.085	32.207	30.400
2007Q4	0.388	0.134	1.319	1.113	0.152	0.148	39.247	38.162
2008Q1	0.456	0.149	1.526	1.397	0.067	0.073	36.550	35.571
2008Q2	0.445	0.149	1.673	1.686	0.139	0.162	34.064	33.252
2008Q3	0.367	0.121	1.863	2.023	0.228	0.261	32.596	31.669
2008Q4	0.361	0.117	2.209	2.443	0.362	0.406	43.785	42.494
2009Q1	0.740	0.235	2.642	3.021	0.127	0.168	37.784	34.034
2009Q2	0.767	0.258	3.117	3.369	0.296	0.379	34.935	31.070

Note: 1. Average OTD loans ratio is measured as quarterly average of 1-4 family residential mortgage loans intended for resell divided by total 1-4 family mortgage loans.
2. The NPLs ratio is the non-performing loans to total assets. The net charge-offs ratio is the net charge-offs of mortgage loans to total mortgage loans. Both ratios are reported in the percentage. Z-Score is defined as the ratio of the return on assets plus the capital ratio divided by the standard deviation of the return on assets. The lower the z-Score is, the more stable the bank is.

Finally, the mean value of z-Score of large banks is lower than that of small banks, which support our findings that large banks are more stable than small banks. This also can be explained by the fact that small banks are highly engaged in the OTD model since the average OTD loans ratio for small banks is relatively larger than large banks (61% for small banks vs 13% for large banks in 2006Q3 and 77% for small banks vs 26% for large banks in 2009Q2).

7.3 Model Specification

Purnanandam (2011) suggests that banks with a high volume of originated OTD loans before the financial crisis seem to be much riskier, leading to a higher default rate and net-charge offs. Therefore, we follow his method to measure the level of OTD lending bank tend to achieve during pre-crisis period and expect the OTD lending is positively associated with bank risk-taking.

Secondly, banks' business model also has an influence on bank risk. One main indicator of business mix is the share of non-interest income to total income. The higher non-interest income to total income banks have, the less risky they are. This is because higher non-interest income indicates income diversification of banks and makes them less dependent on traditional business (Boyd et al., 1980). Conversely, Demirgüc-Kunt and Huizinga (2010) and Altunbas (2011) suggest that banks with a higher share of non-interest income are more risky. Therefore, it is necessary that we include this variable to test the impact of banks with a high share of non-interest income over total income on bank stability. Alternatively, the loan ratio, measured as the ratio of loans to total assets, also can be used as an indicator as business mix because a larger portfolio of loans is more likely to have a greater exposure to credit risk (Maudos and de Guevara, 2004).

Thirdly, bank risk taking also depends on other bank characteristics, so based on the literature the regression also includes a set of control variables which influence bank riskiness, such as bank size, capital, deposits and liquidity. Bank size is measured as the natural logarithm of total assets in the regression model to capture the impact on bank risk taking through many possible channels, such as funding and risk management opportunities (Casu et al., 2011). Moreover, the large banks can have better access to the OTD market to get sufficient external funds (Loutskina, 2005) and they may also have superior risk management systems to diversify risk (Demsetz and Strahan, 1997).

Bank capital ratio is included in the model because capital is considered as “a buffer of uninsured private funds to absorb portfolio losses” (Avery and Berger, 1991). Moreover, capital-constrained banks tend to have a lower screening and monitoring incentive (Thakor, 1996; Holmstrom and Tirole, 1997), so banks with capital constraints are more likely to be more risky. Therefore, we expect that banks with more capital are less risky.

In general, there are two possible ways that demand deposits can influence bank risk-taking behavior. On the one hand, in the presence of deposit insurance, banks with larger amount of demand deposits tend to encourage imprudent risk-taking behavior of banks. Calomiris and Kahn (1991) and Flannery (1994) provide theoretical evidence that demand deposits can control imprudent risk-taking activities of a bank. On the other hand, demand deposits can also act as a disciplining device since large-scale inefficient withdrawal by the depositors can pose a threat to bank stability, reducing banks' risk-taking behavior. Diamond and Rajan (2001) show that demand deposits can act as a disciplining to avoid taking undesirable risk. In addition, it is well known that banks with higher share of liquid assets are less risky since liquid assets can be used as a buffer against liquidity shocks (Cornet et al., 2011), so we would expect that bank liquidity is positively associated with bank stability.

Fourthly, we include real GDP growth in the model as a macroeconomic indicator to account for the impact of variation of macroeconomic conditions on bank risk because unemployment and insolvency rates will be much lower in good economic conditions, reducing credit risk of banks' loan portfolio (Köhler, 2012). Furthermore, projects in the loan portfolios of banks will have a better performance in better economic conditions, reducing overall credit risk of banks (Kashyap et al., 1993). Finally, to deal with endogeneity problems, we also use lagged changes in the explanatory variables and add a lagged dependent variable.

Thus, we estimate the following model to conduct our tests:

$$Risk_t = \alpha_3 + \beta_1 Preotd_{it} + \beta_2 NNI_{it-1} + \sum_{j=1}^{5} \vartheta_j X_{jt-1} + \gamma \Delta lnGDP_t + \beta_3 Risk_{t-1} + \varepsilon_{i1t}$$

The dependent variable is bank risk which is measured in three ways. We first use non-performing loans as a proxy for default rate of banks. We use the ratio of mortgage loans which are delinquent for more than 30 days to total mortgage loans to measure the default rate of mortgage loans. [23] We expect that banks with more OTD loans originated before the financial crisis were more likely to suffer higher default rate. Second, when the number of non-performing loans begins to increase, banks actually have to cover potential losses associated with those loans through a loan losses and provisions account. Non-performing assets

[23] We consider total loans that are past due 30 days or more and are non-accruing as non-performing loans.

remain on the balance sheet even though banks have already recognized losses associated with these loans, but are not on the balance sheet until the banks actually "write off" these loans as net charge-offs. Therefore, we also use the ratio net charge-offs of total mortgage loans to measure bank risk. Net charge-offs are calculated by the charge-offs minus net recoveries of 1-4 family residential mortgage loans. We expect banks involved in the OTD model before the crisis to have higher net charge-offs. Third, we use z-score to measure bank risk (Boyd et al., 1993). The z-score has been widely used as indicator of distance to default. It is defined as the ratio of the return on assets plus the capital ratio divided by the standard deviation of the return on assets. More specifically, insolvency is defined when there is not enough equity which can absorb the losses ($E < -\pi$, where E is equity and π is profit), then the probability of insolvency can be written as prob (-ROA< CAR) where ROA (ROA=π /A) is return on assets and CAR (CAR=E/A). If profits are normally distributed, then the inverse of probability of insolvency can be expressed as following equation:

$$Zscore_{it} = \frac{ROA_{it} + CAPITAL_{it}}{SDROA_i}$$

where SDROA is the standard deviation of return on assets. As the z-score is the inverse of the probability of bank insolvency, a high value of z-score indicates that banks take fewer risks and are more stable. The return on assets and standard deviation of return on assets are calculated in the window of four quarters. We use the natural logarithm of the z-score since it is highly skewed. We expect that banks active in the OTD lending before the financial crisis would have higher probability of default. Since a high z-Score indicates that banks are more stable, we expect that the effect of the OTD lending is significantly negative on bank stability.

Following Purnanandum (2011), we take the average value of origination ratio for every bank during 2006Q3, 2006Q4, 2007Q1 and 2007Q2 to measure the level OTD of lending which banks are intended to achieve before the financial crisis. [24] This variable is denoted by $Preotd_{it}$. NNI is the share of non-interest income to total income to reflect bank business strategy. The vector X_{jt-1} describes additional bank characteristics which are included in the model to control the possible impact on bank risk taking, such as total assets, total loans, deposits, capitals, liquid assets. Total asset is the natural logarithm of total assets at the beginning of a quarter. Loan ratio is the share of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the

[24] We take the average of OTD ratio during the 2006Q3, 2006Q4, 2007Q1 2007Q2 to measure the level of OTD lending banks tend to achieve as residential mortgages market has tightened considerably over most of the period 2007:Q3–2009:Q2 (Federal Reserve Board, 2010).

ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. $\Delta lnGDP_t$ is the quarterly changes in the logarithms of the real GDP of US. The real GDP is collected from the U.S. Bureau of Economic Analysis and calculate the quarterly changes of logarithms of the real GDP as an indicator of macroeconomic conditions. In addition, we also add a BHC dummy variable that equals one if the bank is part of a single-bank holding company, two if it is affiliated with a multi-bank holding company and zero otherwise (Ashcraft, 2008).

7.4 Empirical Results

Table 7.2 reports estimation of the relationship between the OTD model and bank risk measured by non-performing loan ratio. The coefficient on Preotd is found to be positive and significant at the 10% level for low-OTD banks in Model 1, which indicates a positive relationship between OTD model of lending and bank risk for low-OTD banks. This result is more significant at the 5% level after we exclude banks with total assets more than 10 billion in Model 2. Furthermore, we find a positive and significant coefficient on the Preotd term for high-OTD banks in Model 3 and the result remains significant after we exclude large banks in Model 4. This is consistent with Purnanandam (2011) that

OTD loans originated before financial crisis are more likely to be non-performing. As expected, there is a positive and significant coefficient on the term of loan ratio for high-OTD banks, which suggests a larger portfolio of loans is associated with banks having higher risk exposure. This could be explained by banks lowering their lending standards and making more loans to riskier borrowers, triggering a higher default rate (Demyanyk and Hemert, 2009, Mian and Sufi, 2009 and Dell' Ariccia et al., 2012).

Table 7.3 reports estimation of the impact of OTD model of lending on bank risk which is measured by the net charge-offs of mortgage loans based on banks with different involvement in the OTD market. The coefficient on Preotd is found to be positive and significant for both low- and high-OTD banks, indicating that the OTD model has a detrimental effect on bank risk taking for those two groups, leading to an increase in net charge-offs. This is consistent with Purnanandam (2011) who suggests that banks with more OTD loans originated before financial crisis tend to have a higher net charge-offs. We also observe a positive and significant relationship between bank size and net charge-offs, which indicates that large banks are likely to have more net charge-offs. Not surprisingly, the parameter estimate on the deposit shows a negative relationship between deposits, which indicates that banks with lower deposits largely rely on non-deposit and wholesale funding, lending to an increase in net charge-offs.

Table 7.2: OTD lending and non-performing loans for low- and high-OTD banks
This table reports the estimates of non-performing loans on OTD indicator, non-interest income, and bank characteristics based on banks' involvements in the OTD model from 2006Q3 to 2009Q2. Preotd is the average value of mortgage loans origination for resell divided by the beginning of period total mortgage loans before 2007Q3. Non-interest income is the share of non-interest income to total income. Total assets ratio is the log value of beginning of quarter total assets. Loan is the ratio of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. The model is estimated by the system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first–difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) Low-OTD banks excluding large banks	(3) High-OTD banks	(4) High-OTD banks excluding large banks
Preotd	0.004*	0.005**	0.002**	0.002**
	(1.84)	(2.18)	(2.58)	(2.33)
Noninterest	-0.002	-0.000	-0.003	-0.003
	(-0.48)	(-0.08)	(-1.26)	(-0.80)
LogTA	0.001	0.001**	0.001*	0.001
	(1.23)	(2.50)	(1.67)	(1.52)
Loan	0.002	0.004	0.010**	0.011*
	(0.45)	(0.68)	(2.39)	(1.70)
Capital ratio	0.001	0.009	0.002	0.015
	(0.08)	(0.55)	(0.11)	(0.74)
Deposit ratio	-0.006	-0.010	-0.016	-0.025*
	(-0.73)	(-1.25)	(-1.53)	(-1.71)
Liquid ratio	0.002	0.009	0.000	-0.004
	(0.36)	(1.36)	(0.05)	(-0.48)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
cons	-0.008	-0.020**	-0.012	-0.018
	(-0.88)	(-2.12)	(-1.47)	(-1.52)
Observations	3531	3345	3584	3064
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.380	0.534	0.861	0.845
Hansen test(p-value)	0.341	0.406	0.457	0.391

Table 7.3: OTD lending and net charge-offs for low- and high- OTD banks

This table reports the estimates of net charge-offs on OTD indicator, non-interest income, and bank characteristics based on banks' involvements in the OTD model from 2006Q3 to 2009Q2. Preotd is the average value of mortgage loans origination for resell divided by the beginning of period total mortgage loans before 2007Q3. Non-interest income is the share of non-interest income to total income. Total assets ratio is the log value of beginning of quarter total assets. Loan is the ratio of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. The model is estimated by the system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) Low-OTD banks excluding large banks	(3) High-OTD banks	(4) High-OTD banks excluding large banks
Preotd	0.004***	0.005***	0.001***	0.001***
	(3.21)	(2.96)	(3.30)	(3.00)
Noninterest	-0.003	-0.004	0.001	0.000
	(-1.64)	(-1.57)	(1.22)	(0.21)
LogTA	0.000*	0.001*	0.001***	0.000*
	(1.75)	(1.83)	(5.12)	(1.73)
Loan	0.003*	0.001	0.003**	0.002
	(1.80)	(0.64)	(2.10)	(1.55)
Capital ratio	-0.005	-0.017*	0.007	0.007
	(-0.83)	(-1.86)	(1.14)	(1.22)
Deposit ratio	-0.006**	-0.015***	-0.008***	-0.010***
	(-2.00)	(-2.72)	(-2.69)	(-2.98)
Liquid ratio	-0.002	0.003	0.000	0.001
	(-0.99)	(0.92)	(0.17)	(0.75)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
cons	-0.005	-0.005	-0.011***	-0.006*
	(-1.41)	(-1.05)	(-3.92)	(-1.76)
Observations	3531	3345	3584	3064
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.141	0.293	0.229	0.143
Hansen test(p-value)	0.299	0.356	0.675	0.544

Table 7.4: OTD lending and bank stability for low- and high- OTD banks

This table reports the estimates of on OTD indicator, non-interest income, and bank characteristics from 2006Q3 to 2009Q2. Preotd is the average value of mortgage loans origination for resell divided by the beginning of period total mortgage loans before 2007Q3. Non-interest income is the share of non-interest income to total income. Total assets ratio is the log value of beginning of quarter total assets. Loan is the ratio of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. The model is estimated by the system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low-OTD banks	(2) Low-OTD banks excluding large banks	(3) High-OTD banks	(4) High-OTD banks excluding large banks
Preotd	-0.177*	-0.248**	-0.080**	-0.081**
	(-1.80)	(-2.39)	(-2.22)	(-2.20)
Non-interest income	0.211	0.115	-0.044	-0.100
	(0.94)	(0.42)	(-0.27)	(-0.55)
LogTA	-0.044*	-0.078**	-0.021	-0.063*
	(-1.74)	(-2.37)	(-1.10)	(-1.86)
Loan	0.454*	0.353	0.174	0.218
	(1.80)	(1.26)	(0.73)	(0.78)
Capital ratio	1.555*	2.065**	1.432*	1.255
	(1.87)	(2.06)	(1.76)	(1.51)
Deposit ratio	-0.265	0.007	1.531**	1.267*
	(-0.51)	(0.01)	(2.17)	(1.77)
Liquid ratio	0.778**	0.390	0.137	0.153
	(2.07)	(0.95)	(0.39)	(0.39)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
cons	0.563	1.120**	0.363	0.983
	(1.24)	(2.11)	(0.77)	(1.47)
Observations	3531	3345	3584	3064
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.036	0.166	0.586	0.923
Hansen test(p-value)	0.368	0.376	0.276	0.59

It can be seen that there is a negative relationship between the OTD model of lending and z-Score as indicated by the significant negative coefficient of preotd term. Our results indicate that banks that are more active in the OTD model have relatively lower z-Score and are more likely to be insolvent for both low- and high-OTD banks. Furthermore, the results remain significant and negative in Model 2 and Model 4 after banks with total assets more than 10 billion are excluded. Our findings are consistent with previous empirical research (Purnanandam, 2011, Bedendo and Bruno, 2012) that the OTD model has a negative effect on bank stability. This indicates that banks originating too many OTD loans before the crisis and have experienced high default rate and net charge-offs, making them more distressed and more likely to become insolvent. Moreover, we find evidence that bank characteristics affect bank stability as indicated by a significant and positive coefficient for capital ratio, which implies that banks with more capitals are less risky in both low- and high-OTD banks as regulatory capital can be used against bank insolvency. Our results also suggest that low-OTD banks with more liquid assets and high-OTD banks with a larger amounts of demand deposits are more stable. This is consistent with banks having greater liquidity being unlikely to be insolvent since demand deposits and liquid assets can be a buffer for adverse shocks (Cornett at al., 2011).

Table 7.5: OTD lending and bank risk for small and large banks

This table reports the estimates of on OTD indicator, non-interest income, and bank characteristics from 2006Q3 to 2009Q2. Preotd is the average value of mortgage loans origination for resell divided by the beginning of period total mortgage loans before 2007Q3. Non-interest income is the share of non-interest income to total income. Total assets ratio is the log value of beginning of quarter total assets. Loan is the ratio of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. The model is estimated by the system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	NPL ratio		Net charge-off ratio		z-Score	
	(1)	(2)	(3)	(4)	(5)	(6)
	Small banks	Large banks	Small banks	Large banks	Small banks	Large banks
Preotd	0.059***	0.001	0.001**	0.001	-2.788***	-0.054
	(2.72)	(0.58)	(2.17)	(1.09)	(-3.38)	(-0.57)
Non-interest income	0.002	-0.010**	0.000	-0.001	0.808	0.117
	(0.15)	(-2.47)	(0.19)	(-0.63)	(1.60)	(0.51)
LogTA	0.017***	-0.000	-0.000	0.001***	-0.920***	-0.041*
	(2.95)	(-0.43)	(-0.64)	(5.62)	(-3.90)	(-1.69)

Loan	-0.012	-0.001	-0.001	0.004**	0.541	0.242
	(-0.44)	(-0.32)	(-0.34)	(2.08)	(0.60)	(0.83)
Capital ratio	-0.048	-0.014	-0.005	0.003	3.913***	0.739
	(-1.57)	(-0.93)	(-0.84)	(0.37)	(2.73)	(0.80)
Deposit ratio	-0.015	-0.027***	-0.008***	-0.013***	-1.148	-0.151
	(-0.94)	(-2.83)	(-2.63)	(-2.71)	(-1.47)	(-0.28)
Liquid ratio	-0.003	0.001	-0.002	-0.001	0.823	0.227
	(-0.19)	(0.23)	(-0.93)	(-0.22)	(1.15)	(0.62)
BHC flag	Yes	Yes	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes	Yes	Yes
cons	-0.222**	0.010	0.006	-0.014***	13.649***	0.998*
	(-2.45)	(1.19)	(0.90)	(-3.89)	(4.02)	(1.89)
Observations	2925	4090	2925	4090	2925	4090
Wald test (p- value)	0.000	0.000	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.964	0.867	0.455	0.112	0.455	0.105
Hansen test(p-value)	0.591	0.303	0.433	0.265	0.309	0.458

We estimate the relationship between bank riskiness and OTD lending across bank size in table 7.5. It is noticeable that bank risk is positively related to the OTD of lending for small banks as the results are shown in three different risk measures, contributing to higher default rate, higher net charge-offs. We find small banks engaged in the OTD model of lending have lower bank stability, as indicated by a negative and significant coefficient in Model 5. This could be explained by most small banks being more intensively involved in OTD lending relative to large banks. However, we cannot see a significant relationship in all risk measures for large banks. The parameter estimate on the deposit in Models 3 and 4 shows a negative relationship between deposits and bank risk taking for both low- and high-OTD banks, indicating that banks with less deposits tend to rely largely on non-deposit and wholesale funding, leading to an increase in net charge-offs. Bank capital ratio is positively related to bank stability for small banks, as indicated in the estimation of Model 5, which suggests that small banks with higher level of capital are more stable because banks with more capital being unlikely to be insolvent.

Table 7.6: Stuck OTD loans and bank risk for low- and high-OTD banks

This table reports the estimates of the stuck OTD loans, non-interest income, and bank characteristics from 2006Q3 to 2009Q2. Stuck loan ratio is defined as the difference between previous Preotd measure and mortgage loans which cannot sold in the post crisis period divided by the average total mortgage loans during pre-crisis period. Non-interest income is the share of non-interest income to total income. Total assets ratio is the log value of beginning of quarter total assets. Loan is the ratio of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. The model is estimated by the system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	NPL ratio		Net charge-off ratio		z-Score	
	(1) Low-OTD banks	(2) High-OTD banks	(3) Low-OTD banks	(4) High-OTD banks	(5) Low-OTD banks	(6) High-OTD banks
Stuck	0.048*	0.002**	0.004**	0.001**	-0.342*	-0.073**
	(1.66)	(2.02)	(2.09)	(2.17)	(-1.91)	(-2.14)
Noninterest	-0.062*	-0.006*	-0.002	0.004***	-0.260	-0.127
	(-1.66)	(-1.65)	(-0.89)	(3.33)	(-1.34)	(-1.02)
LogTA	0.005*	0.001**	-0.000	0.000**	-0.018	0.009
	(1.82)	(2.28)	(-1.06)	(2.58)	(-0.88)	(0.71)
Loan	0.032	0.012**	0.003	0.002	0.180	-0.063
	(0.71)	(2.29)	(1.38)	(1.41)	(0.92)	(-0.26)

Capital ratio	-0.075	0.033*	-0.006	0.001	0.976	0.815
	(-0.78)	(1.66)	(-0.95)	(0.23)	(1.43)	(1.22)
Deposit ratio	-0.084	-0.009	-0.012**	-0.006*	-0.132	0.555
	(-0.86)	(-0.71)	(-2.31)	(-1.84)	(-0.35)	(1.28)
Liquid ratio	0.066	-0.003	0.004	-0.002	0.410	-0.031
	(0.71)	(-0.30)	(1.34)	(-0.90)	(1.62)	(-0.09)
BHC flag	Yes	Yes	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes	Yes	Yes
cons	-0.060	-0.020**	0.004	-0.005**	0.538	0.129
	(-0.94)	(-2.11)	(1.01)	(-1.97)	(1.45)	(0.34)
Observations	3509	3573	3509	3573	3509	3573
Wald test (p- value)	0.000	0.000	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.911	0.322	0.312	0.233	0.027	0.391
Hansen test(p-value)	0.286	0.372	0.24	0.272	0.235	0.685

Our previous results show that originating a large amount of OTD loans before the financial crisis lead to an increased probability of bank insolvency when mortgage rate changes, capital gains and losses are accrued on the mortgages held on balance sheet and in the sales pipeline. If securitization markets collapse, banks are unable to sell off loans and are forced to hold these loans in the pipeline. Therefore, we also want to examine further whether the OTD loans that were originated during the pre-crisis period but cannot be sold in the secondary market contributed to bank insolvency.

To measure the level of these “stuck loans”, we follow by Purnanandam’s (2011) method and first calculate quarterly averages of OTD loans originated during the pre-crisis periods, i.e., during the quarters 2006Q3, 2006Q4, 2007Q1 and 2007Q2, and the quarterly averages of loans actually sold during the post-crisis periods, i.e., during 2007Q3 to 2009Q2. We scale the difference between them by the average total mortgage loans during pre-crisis period. This variable is defined as the previous Preotd measure subtracting mortgage loans which cannot sold in the post crisis period. It is worth mentioning that this measure is a relatively proper way to proxy stuck loans by using the bank-level data to assess this effect, since we cannot match loan origination with selling data at the loan-by-loan level. This variable enables us to analyse the effect of OTD loans that a bank originated but was unable to sell due to the unexpected drop in liquidity in the secondary market. We use following model to assess the impact of stuck OTD loans on the bank risk and expect that banks that are stuck with more of these loans are more risky:

$$Risk_t = \alpha_2 + \beta_4 Stuck_{it} + \beta_5 NNI_{it-1} + \beta_6 Loan_{it-1} + \sum_{j=1}^{5} \delta_j X_{jt-1}$$
$$+ \gamma_1 \Delta LnGDP_t + \beta_7 Risk_{t-1} + \varepsilon_{i2t}$$

Table 7.6 provides estimations of the effect of stuck OTD loans on bank risk. We find that banks with more OTD loans stuck on balance sheet tend to experience a higher default and net charge-offs for both low- and high-OTD banks. Moreover, we also observe a negative relationship between stuck loans and z-Score as reported in the Model 5 and 6, which implies that banks that were stuck more OTD loans tend to have relative low z-Score, leading to a detrimental effect on bank stability.

Purnannandum (2011) suggests that OTD loans originated in pre-crisis period have a significant effect on mortgage default of banks during the financial crisis. We also want to investigate the effect of OTD lending prior to financial crisis on the bank stability after the crisis for both low- and high-OTD banks. We interact OTD lending with a dummy variable and do not find a significant coefficient on the interaction term, which indicates that OTD lending mainly increases bank instability during the pre-crisis period. Our results can be explained by banks holding more liquid assets and reducing leverage after the Fed the pumped liquidity into the OTD market.

We then follow a similar method to that used by Stiroh and Rumble (2006) to decompose the z-score into two components as alternative indicators of banks risk for robustness testing of our results, giving better understanding of the driving force of banks' risk taking.[25]

For the quarters within a year:

$$PortfolioRisk_{it} = \frac{ROA_{it}}{SDROA_i}$$

$$LeverageRisk_{it} = \frac{CAR_{it}}{SDROE_i}$$

We take the return-on-assets (ROA) of bank i divided by the standard deviation of the return on asset (SDROA), measured over four quarters, as the measure of portfolio risk. Another indicator that reflects the leverage risk is the ratio of bank equity to total assets (CAR) divided by SDROE. Higher ratios indicate that banks are more stable. The results

[25] See a similar method to decompose the z-Score in Lepetit et al. (2008), Demirgüc-Kunt and Huizinga (2010) and Barry et al. (2012).

with our two alternative measures of bank risk are shown in Table 7.6 and Table 7.7.

Consistent with our previous findings, we observe a negative relationship between OTD lending and portfolio risk as reported in Models 1 and 2 of Table 7.6, which indicates that banks involved in the OTD model of lending tend to have higher portfolio risk for both low- and high-OTD banks. We also examine whether the OTD lending can increase portfolio risk across bank size. We find similar outcomes in small banks as indicated by significant and negative coefficient on the Preotd term in Model 3 of Table 7.7 but we cannot find a significant relationship in large banks. In Table 7.8, we can only find significant evidence that the OTD lending increases leverage risk in small banks. This may be explained by banks wanting to sell assets to lower their leverage due to unexpected adverse shocks in good times (Acharya and Viswanathan, 2011).

From Table 7.7, banks with a higher share of non-interest income seems more exposed to portfolio risk expected for small banks as the coefficient of non-interest income ratio is negative and significant, which means that OTD lending not only increases the risk-adjusted return of banks but also increases portfolio risk. We also find a significantly negative relationship between leverage risk and the share of non-interest I ncome in all four regression as shown in Table 7.8, which indicates banks with a high non-interest income share seem to have greater leverage risk. The OTD model is a fee-based business and high engagement in the model allows banks to earn fees but increases the level of portfolio risk and leverage risk.

The coefficient for bank size is significant and negative as shown in the Models 1 and 2 of Table 7.7, indicating that relative large banks have a greater exposure to portfolio risk. We also find that deposit ratio is significantly positively related to low portfolio risk. These results suggest that banks with a large demand deposits base are less exposed to portfolio risk. This is consistent with the fact that banks with more demand deposits would be less dependent on wholesale funding and are likely to use traditional source of funding to finance loans, lowering the exposure to portfolio risk and leverage risk.

Table 7.7: OTD lending and portfolio risk

This table reports the estimates of on OTD indicator, non-interest income, and bank characteristics from 2006Q3 to 2009Q2. Preotd is the average value of mortgage loans origination for resell divided by the beginning of period total mortgage loans before 2007Q3. Non-interest income is the share of non-interest income to total income. Total assets ratio is the log value of beginning of quarter total assets. Loan is the ratio of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. The model is estimated by the system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Portfolio risk		Portfolio risk	
	(1)	(2)	(3)	(4)
	Low-OTD banks	High-OTD banks	Small banks	Large banks
Preotd	-0.589***	-0.173***	-0.159***	0.032
	(-3.08)	(-3.45)	(-3.24)	(0.27)
Non-interest income	-0.443**	-0.683***	-0.137	-0.815***
	(-2.21)	(-2.96)	(-0.52)	(-3.81)
LogTA	-0.080**	-0.060***	0.107	-0.011
	(-2.01)	(-2.71)	(1.21)	(-0.39)
Loan	-0.242	-0.473	-0.393	-0.051
	(-0.75)	(-1.33)	(-0.89)	(-0.14)
Capital ratio	0.934	-0.175	1.795	-0.143
	(0.92)	(-0.13)	(1.25)	(-0.11)
Deposit ratio	1.312	2.387**	2.040**	2.243**
	(1.40)	(2.50)	(2.29)	(2.35)
Liquid ratio	0.750	0.470	0.383	0.839*
	(1.53)	(1.01)	(0.66)	(1.69)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
cons	1.230*	1.488**	-1.284	0.427
	(1.70)	(2.34)	(-0.91)	(0.58)
Observations	3531	3584	2925	4090
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.733	0.222	0.900	0.218
Hansen test(p-value)	0.332	0.269	0.423	0.622

Table 7.8: OTD lending and leverage risk

This table reports the estimates of on OTD indicator, non-interest income, and bank characteristics from 2006Q3 to 2009Q2. Preotd is the average value of mortgage loans origination for resell divided by the beginning of period total mortgage loans before 2007Q3. Non-interest income is the share of non-interest income to total income. Total assets ratio is the log value of beginning of quarter total assets. Loan is the ratio of total loans to total assets. Capital ratio is Tier 1 capital as a fraction of total risk-adjusted assets measured at the beginning of quarter. Deposit is the ratio of total demand deposit to total assets at the beginning of quarter. Liquid assets ratio is defined as liquid assets as the fraction of beginning of quarter total assets. The model is estimated by the system GMM approach of Arellano and Bover (1998) and Blundell and Bond (1998). Robust standard errors are in brackets. Wald test is for the mull hypothesis that all coefficients expect constant are zero. MA(1) and MA(2) are Arellano-Bond test for zero autocorrelation in first –difference errors. Hansen test is the test of overidentifying restrictions. ***, **, and * denote that the coefficients are statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Leverage risk		Leverage risk	
	(1)	(2)	(3)	(4)
	Low-OTD banks	High-OTD banks	Small banks	Large banks
Preotd	-6.186	-2.276	-2.400*	-6.499
	(-0.78)	(-1.51)	(-1.83)	(-1.45)
Non-interest income	-32.382***	-21.552***	-12.442*	-28.040***
	(-4.93)	(-3.29)	(-1.67)	(-3.60)
LogTA	-1.176	0.164	-2.121	0.146
	(-0.85)	(0.25)	(-1.07)	(0.14)
Loan	15.789	0.305	25.798**	9.477
	(1.19)	(0.03)	(2.18)	(0.51)
Capital ratio	87.725**	105.122**	56.978	161.659***
	(2.10)	(2.48)	(1.58)	(2.66)
Deposit ratio	42.429	30.363	54.515**	-15.741
	(1.60)	(1.26)	(2.44)	(-0.63)
Liquid ratio	15.435	-12.078	13.415	-5.727
	(0.95)	(-0.73)	(0.79)	(-0.30)
BHC flag	Yes	Yes	Yes	Yes
Market controls included	Yes	Yes	Yes	Yes
Lagged dependent variables included	Yes	Yes	Yes	Yes
cons	24.072	9.864	9.864	8.189
	(0.90)	(0.57)	(0.57)	(0.29)
Observations	3531	3584	2925	4090
Wald test (p- value)	0.000	0.000	0.000	0.000
MA(1) (p-value)	0.000	0.000	0.000	0.000
MA(2) (p-value)	0.995	0.034	0.489	0.204
Hansen test(p-value)	0.252	0.279	0.407	0.577

7.5 Conclusion

We extend the research period through the peak of the financial crisis to investigate the impact of OTD lending on bank risk-taking based on banks' involvements and bank size. Our findings suggest that the OTD lending increases bank risk for both low- and high-OTD banks. More importantly, the increase in bank risk arises mainly from mortgage loans stuck on the balance sheet. We decompose bank risk into portfolio risk and leverage risk. In contract with previous literature, we find that the OTD model mainly contributes to an increase in portfolio risk but not in leverage risk. There is only a significant increase in leverage risk for small banks.

Our results imply that banks with more capital and liquid assets are more stable and have less exposure to portfolio risk and leverage risk, which is in favour that the Basel III framework requiring banks to increase capital and liquidity by posing stricter banks capital, liquidity, and leverage requirements, reducing bank risk-taking behaviour and stabilizing the banking system. Since our results document a disparate effect on bank risk in small and large banks and encouraging small banks to engage highly in OTD lending, increasing their risk-taking and the probability of insolvency, this could suggest to regulators that they need to be aware of small banks involved in the OTD market and increase those requirements related to OTD practice of small banks to make sure that small banks will not take on excessive risk.

Chapter 8

Summary and Conclusion

8.1 Introduction

This chapter presents a summary of our research findings and policy implications about the determinants of using OTD model of lending and the impact of OTD lending on credit supply and bank risk-taking behaviour in US commercial banks. The chapter is organized into six sections as follows. Section 8.2 reviews the research background and outlines our research objectives. In Section 8.3 provides an overview of the methodology used in our study. Section 8.4 summaries the main findings of our research. Contributions are presented in the Section 8.5 and policy implications are in the Section 8.6. Lastly, we discuss the limitations of our research and give some suggestions for future research.

8.2 Background and Research Objectives

Two important fundamental functions of banks have been changed by OTD model: liquidity transformation (Diamond and Dybvig, 1983) and delegated monitoring (Diamond, 1984). As banks are able to offload loans from balance sheet, they rise funding through selling loans to finance loans and liquidity (Diamond and Rajan, 2001; Loutskina and

Strahan, 2009; Loutskina, 2011). Therefore, banks seem to be less dependent on traditional source of funding, such as deposits. In addition, banks tend to lower incentives to monitor borrowers after selling loans from their balance sheets (e.g. Pennacchi, 1988; Gorton and Pennacchi, 1995; Key et al., 2010; Purnanandam, 2011). It is very important to know why banks are engaged in the OTD model - the literature scarcely discusses the motivations for OTD lending across banks with different intensities of involvements in the OTD model and across bank size. Therefore, our first research objective was to investigate the incentives for using the OTD model of lending. This addresses the following questions: 1) What motivates banks to become engaged in the OTD lending for low- and high-OTD banks? 2) Do small banks and large have similar incentives to use OTD model of lending?

Moreover, the literature has intensively discussed the impact of OTD model on the supply of loans. Banks tend to decrease lending standards and lend to more risky borrowers after they sell loans from their balance sheets, leading to an expansion of aggregate credit supply (Dell' Ariccia and Marquez, 2006; Demyanyk and Hemert, 2009; Mian and Sufi, 2008; Dell' Ariccia et al., 2010). Conversely, Loutskina and Strahan (2009) and argue that the OTD model enables banks to obtain balance sheet liquidity and increases their willingness to provide more credit. Loutskina (2011) finds that the OTD model allows banks to hold less liquid assets and make more loans, making banks less sensitive to cost of funding shocks. Besides that, our findings also indicate that banks tend to consider the OTD model of lending as a funding and liquidity provider. The next research objective was to examine whether this positive effect varies across banks with different levels of involvements in the OTD model and bank size. This leads to the following questions 3) Does OTD lending lead to a significant increase in loan supply across banks with different levels of involvements in the OTD model? 4) Do small banks and large banks that are active in the OTD lending seem to have a significant increase in loan growth?

Finally, there is a growing literature about the impact of the OTD model on bank risk. It is argued that banks tend to decrease lending standards and lend to more risker borrowers, triggering a deterioration of loan portfolios (Dell'Ariccia and Marquez, 2006; Dell' Ariccia et al., 2010; Mian and Sufi, 2009). Moreover, recent studies indicate that the OTD model contributes to lower monitoring incentives of their borrowers after loan sale, resulting in higher default rate of securitized loans (Parlour and Plantin, 2008; Bubb and Kaufman, 2009, Keys et al., 2010; Purnanandam, 2011). On the other hand, the OTD model can be used as a tool for risk management to transfer risk (Cebenoyan and Strahan, 2004) and it plays a positive role in bank risk management, reducing insolvency risk (Jangli and Pritsker, 2008). Thus, the net impact of the

OTD model of lending on risk-taking behaviour of banks is ambiguous. It is important to clarify the impact of OTD lending on bank risk-taking behaviour. The finial research objective is to investigate whether OTD lending contributes to an increase in bank risk. This addresses the two questions 5) Does OTD lending have a positive impact on bank riskiness in low- and high-OTD banks? 6) Does OTD lending have different effects on risk-taking of small and large banks? The following table 8.1 summarizes those questions which we come up with and related answers.

Table 8.1 Research questions and related answers

Research Questions	Answers
Question 1: What motivates banks to become engaged in the OTD lending for low- and high-OTD banks?	Both low- and high-OTD banks with more OTD mortgage loans, lower quality of mortgage loans would use OTD model of lending. In addition, releasing funding and liquidity problems would be main motivations for high-OTD banks.
Question 2: Do small banks and large have similar incentives to use OTD model of lending?	No. Both small and large banks with more OTD mortgage loans, poor performance of mortgage loans tend to use OTD model of lending. In addition, small banks with higher funding cost, less liquid assets and capitals appear to use OTD lending.
Question 3: Does OTD lending lead to a significant increase in loan supply across banks with different levels of involvements in the OTD model?	No. OTD model of lending leads to an increase in the supply of credit for high-OTD banks but not for low-OTD banks.
Question 4: Do small banks and large banks that are active in the OTD lending seem to have a significant increase in loan growth?	Yes. OTD lending has positive impact on credit supply for both small and large banks.
Question 5: Does OTD lending have a positive impact on bank riskiness in low- and high-OTD banks?	Yes. OTD lending increases bank risk for both low- and high- OTD banks.
Question 6: Does OTD lending have different effects on risk-taking of small and large banks?	Yes. OTD lending has an adverse effect on bank stability for small banks but not for large banks.

8.3 Overview of Research Method Employed

The two most commonly methods for panel data analysis are Fixed Effect Estimator and SGMM estimator. We use both to study the determinants of OTD lending and its impact on credit supply. Since the time invariant variables cannot be estimated in a Fixed Effect Model, we do not employ it to estimate the impact of OTD lending on bank risk-taking behaviour. The Hausman test results show that individual effects exist in the model specification and Fixed Effects Model with "within" transformation technique is used to remove fixed effects. Moreover, a Fixed Effects estimator is biased in the dynamic panel model due to the correlation between error terms and lagged dependent variables, so an SGMM estimator is used to address this endogenity problem by instrumenting the predetermined and endogenous variables with their own lags. Moreover, SGMM is more appropriate for unbalanced data and two-step SGMM is more efficient (Roodman, 2009). The results from Fixed Effect Model as robustness tests are similar as those we get from SGMM Estimator. In the next section, we will provide a summary of our main research findings.

8.4 Summary of the Findings

Table 8.2 summarizes the hypotheses and key findings of our research. The main findings are shown below:

Chapter 5 examines the determinants of OTD lending vary across banks with different intensities of involvements in the OTD model and across bank size. The results show that banks with more originated OTD loan tend to sell them from their balance sheets. Banks with poor performance of mortgage loans also are more likely to be engaged in OTD lending since they may have an incentive to sell those loans. We also find that banks have different incentives to be involved in OTD lending. High-OTD banks resort to the OTD model so as to provide an additional source of funding to finance loans and liquidity when they face high cost of funding and liquidity constraints. In addition, small banks seem to use the model to alleviate capital requirements since they are less capitalized than large banks. Besides that, they are more likely to rise funding through the OTD model relative to large banks when they face higher cost of funding. Finally, our findings indicate that OTD model of lending still can be used during the financial turmoil, especially when market conditions are most server in 2008Q4, so the Fed tends to preserve liquidity in the OTD markets to make sure that financial institutions can obtain liquidity through the OTD model. Therefore, this study concludes that funding and liquidity needs are two additional motivations for high-OTD banks and small banks to be involved in the OTD model. Besides that, regulatory capital arbitrage is particularly important for small banks.

Chapter 6 investigates the impact of OTD lending on credit supply. Our findings suggest that the OTD model can contribute to a significant increase in high-OTD banks as they tends to rise funds through selling off loans rather than financing loans by deposits. This also confirms our previous results that the OTD lending allows high-OTD banks to shed from high cost of funding and meet their liquidity needs. The study also documents similar findings in the small and large banks and further finds that there is no significant relationship between OTD lending and loan growth after the financial crisis. This implies that banks use the OTD model to obtain liquidity and seem to hoard liquidity rather than supply

Table 8.2: Summary of Hypotheses and Key Findings

Hypotheses	Relationship	Findings	Remarks
H5.1: Banks with more mortgage loans intended for resell are more likely to sell these loans in the secondary market.	Positive and significant	Banks that originated more OTD mortgage loans and are more likely to sell these loans from their balance sheets.	Significant in low-OTD, high-OTD, small and large banks
H5.2: Poor performance of mortgage loans motivates banks to offload loans from their balance sheets.	Positive and significant	Banks with more non-performing mortgage loans have more incentive to be engaged in the OTD model of lending.	Significant in low-OTD, high-OTD, small and large banks
H5.3: Banks seem to be engaged in the OTD lending when they face high cost of funding.	Positive and significant	Banks with high cost of funding tend to use the OTD lending to provide an additional source of funding.	Significant in low-OTD, high-OTD, small and large banks
H5.4: Banks facing liquidity constraints or having liquidity shortfalls are more likely to employ the OTD model to obtain liquidity.	Negative and significant	Banks with less liquid assets are active in the OTD lending to meet their liquidity needs.	Significant in high-OTD and small banks
H5.5: Capital-constrained banks are more likely to be involved in the OTD market to free some capital.	Negative and significant	Banks with less capital seek to use the OTD model to alleviate capital requirements.	Significant in small banks

H6.1: OTD lending has a positive impact on the loan supply.	Positive and significant	Banks involved in the OTD model show a significant increase in the supply of credit.	Significant in high-OTD, small and large banks
H6.2: OTD lending has changed the relationship between changes of monetary policy and bank lending channel.	Positive and significant	The impact of changes of monetary policy on bank lending channel is positive under OTD lending.	Significant in high-OTD and small banks
H7.1: Banks highly involved in the OTD lending seem to be more risky.	Positive and significant	Banks with more OTD loans originated before the financial crisis are more likely to suffer higher default rate and higher net charge-offs.	Significant in low-OTD, high-OTD, small and large banks
H7.2: Banks that originated more OTD mortgage loans tend to higher probability of insolvency.	Negative and significant	Banks that are active in the OTD market seem to be less stable as indicated by the lower level of z-Score.	Significant in low-OTD, high-OTD, small and large banks
H7.3: The OTD model of lending has a positive impact on the portfolio risk of banks.	Negative and significant	Banks engaged in OTD lending have a significant increase in portfolio risk.	Significant in low-OTD, high-OTD and small banks
H7.4: The OTD model of lending has a positive impact on the leverage risk of banks.	Negative and significant	The increase in leverage risk of banks results from high involvement in the OTD model.	Significant in small banks

loans during the financial downturn. Our results also show a negative relationship between loan performance and loan growth. This implies that banks lower lending standards and lend to riskier borrowers, lending to a higher default of mortgage loans. Thus, poor loan performance results from an increase in the supply of credit. Finally, this study provides evidence about positive effects of changes of monetary policy on the bank lending channel through the OTD business model, especially in high-OTD banks and small banks as they are intensively involved in the OTD model.

Chapter 7 studies the impact of OTD lending on bank risk-taking behaviour. Three means are adopted to measure bank riskiness. Our results indicate that bank that active in the OTD model of lending, both low- and high-OTD banks, are more likely to have higher default rate and net charge-offs of mortgage loans. Our findings also show that OTD lending increases probabilities of bank insolvency for low- and high-OTD banks. This implies banks engaged in the OTD lending appear to have a lower level of Z-score. In addition, our findings show that small banks that engaged in the OTD model are more likely to suffer higher default risk and be less stable relative to large banks. This could be explained by the higher average OTD mortgage loans ratio which indicates that small banks appear to be more active in the OTD model than large banks. Finally, we decompose the Z-score into two components and further assess whether the OTD lending has a positive effect on portfolio risk and leverage risk. Our findings suggest that it has a significant and positive impact on portfolio risk but not significant for leverage risk.

8.5 Contributions of the Study

The main objective of this research is to investigate the determinants of the OTD model of lending and its impact on the supply of credit and bank risk. The contributions of this study can be found in the relevant chapters. In this section, we highlight our main contributions of our research:

First, the study extends the current literature and provides an understanding of the incentives for employing OTD lending and its impact by examining banks across different intensities of involvements in the OTD model and across bank size.

Second, our research focuses on one asset class in the OTD model, 1-4 family residential mortgage loans, which account for the majority of OTD lending whereas other existing studies pay more attention to a single instrument of the OTD model, normally loan sale or securitization. In particular, we focus on driving forces for employing OTD lending at the frontend of the securitization channel at originating bank level. Our results are consistent with existing literature about the motivation of OTD model of lending suggesting that regulatory capital arbitrage, credit risk transfer and liquidity needs are the main reasons for being involved in OTD lending. Specifically, banks with more originated OTD loans, higher share of risky mortgage portfolio, high cost of funding and less liquid assets tend to use OTD lending. Moreover, the results are in favour of the regulatory arbitrage hypothesis that OTD model can be used by small banks to alleviate regulatory capital requirements as they seem to be capital-constrained.

Third, our study gives a comprehensive understanding of the impact of OTD lending on credit supply. There are almost no papers assessing the impact of OTD lending on credit supply across different levels of involvement in the OTD model. We examine its impact across bank size and across business cycle. More importantly, we examine this effect at the frontend of securitization channel at originating bank level whereas other existing studies investigate the impact of OTD activities during the process of securitization. Our research contributes to existing literature that OTD lending plays a positive role on credit supply. Our findings also provide evidence that the OTD lending model has changed the link between changes of monetary policy and loan supply.

Fourth, we shed more light on the relationship between the OTD model of lending and bank risk-taking behaviour. This study contributes to existing literature by assessing the impact of the OTD model of lending on bank riskiness across banks with different intensities of involvements in OTD lending. Our findings clarify that the OTD model of lending increases bank risk-taking for both low- and high-OTD banks. In addition, we show that small banks involved in the OTD market are more likely to suffer default and be less stable relative to large banks. This implies that regulators should pay more attention to small banks which are more active in the OTD model of lending than large banks. A disparate effect on the bank risk taking among two groups suggests that regulators need to treat them differently to avoid 'one size fits all' in bank regulation, re-establishing a sustainable OTD framework.

8.6 Policy Implications

Our study provides a comprehensive understanding of the incentives for employing the OTD model and its impact on credit supply and bank risk-taking. We document a positive effect of changes of monetary policy on bank lending channel under the OTD lending. This allows bank regulatory authorities to understand the transmission mechanisms of monetary policy on the bank lending channel in the context of the OTD model. Moreover, it provides a better understanding of the OTD model, knowing clearly whether that model of lending has provided a way of reducing bank risk. Our findings suggest that small banks active in the OTD model are more risky relative to large banks as they are more intensively involved in the model relative to large banks. This suggests that regulators need to treat two groups differently to avoid 'one size fits all' in the bank regulation, building re-establish a sustainable OTD framework.

Our research examines whether the Dodd-Frank Act and Basel III are suited to rebuilding the OTD framework. Our results imply that banks with higher levels of non-performing mortgage loans tend to offload more loans from balance sheet and those loans sold to third parties have a higher default risk relative to retained loans (Affinito and Tagliaferri, 2010; Agarwal et al., 2012). This suggests that regulators not only promote adequate risk retention than required by the Dodd-Frank Act to enhance monitoring and screening incentives, but also banks should disclosure some information about mortgage loans which are sold to other parties, increasing transparency of OTD practices and reducing incentive to sell riskier loans to securitization pool. In addition, the Basel III framework has been proposed to reduce banks' risk-taking behaviour by increasing capital, liquidity and leverage requirements after the financial crisis. Meanwhile, it prevents banks from making use of the OTD model of lending, leading to a decrease in credit supply (Bank for

International Settlements, 2011). Our findings suggest that it is not an optimal solution for regulators to stabilize banking system by excessively downsizing the OTD model of lending because it can provide credit supply to the whole economy.

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Appendix

Table A.1: Variable Definitions

Variables	Variable Description	Data term from Call Report
OTD Model of Lending		
Origination	The OTD lending contains two categories: retail origination and wholesale origination. We divide the sum of retail and wholesale origination by the beginning of the quarter total mortgage loans as a measure of OTD in our analysis. Preotd is calculated as the average value of origination ratio before 2007Q3.	(RCONF066+RCONF067+RCONF068+RCONF069+ RCONF670+RCONF671 +RCONF672+RCONF673)/RCON1430
Loan sales	The ratio is defined as 1–4 family residential mortgage loans sold to third parties during the quarters scaled by total mortgage loans for 1–4 family residential at the beginning of the quarter.	(RCONF070+RCONF071+RCONF674+RCONF675)/ RCON1430

Balance Sheet Items		
Liquidity ratio	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. The liquidity ratio is the ratio of liquid asset to total assets.	(RCFD0010+RCONB987+RCFD0211 RCFD1287+RCFD1289+RCFD1293+RCFD1294+RCFD1298)/RCFD2170
Cost of funding	Interest Expense/ Total Liabilities	RIAD4073/RCFD2948
Loan ratio	Total Loan/ Total assets	RCFD1400/RCFD2170
Return on Assets	Income Before Extraordinary Items and Other Adjustments/ Total Asset	RIAD4300/RCFD2170
Non-interest income ratio	Non-interest Income / Net Operating Revenue	RIAD4079/(RIAD4074+RIAD4079)
Non-performing mortgage loans	We consider 1-4 family residential mortgage loans that past due 30 days or more and are non-accruing as non-performing mortgage loans. The ratio is computed as non-performing mortgage loans divided by total 1-4 family residential mortgage loans	(RCON5398+RCON5399+RCON5400 +RCONC229+RCONC230+RCONC236 +RCONC237+RCONC238+RCONC239)/RCON1430
Capital Ratio	Risk-weighted Assets/Total Assets	RCFDA223/RCFD1400
Deposit Ratio	Demand Deposit/ Total Assets	RCFD2200/RCFD2170

C&I Loans Ratio	The ratio is calculated as the sum of C&I loans and agricultural loans divided by total assets.	(RCFD1600+RCFD1590)/RCFD2170
Risk Measures		
Non-performing Loans Ratio	We take loan that past due 90 days or more as non-performing loans. Non-performing ratio is measured as non-performing loans divided by total loans.	(RCFD1407+RCFD1403)/RCFD1400
Net Charge-offs Ratio	Net charge-offs ratio is measured as the difference between charge-offs and net recoveries of 1-4 family residential mortgage loans divided by total 1-4 family residential mortgage loans.	(RIAD5411+RIADC234+RIADC235)-(RIAD5412+RIADC217+RIADC218)/RCON1430
z-Score	z-Score=(ROA+CAPITAL)/SDROA. The ratio is calculated over past four quarter. In order to compute this ratio, we extend our sample backwards to 2005Q3.	

Table A.2: Ten largest origination banks in U.S

Number	RSSD9001	Entity name (RSSD9010)
1	451965	WELLS FARGO BANK
2	852218	JPMORGAN CHASE BANK
3	480228	BANK OF AMERACAN
4	476810	CITIBANK
5	570231	COLONIAL BANK
6	675332	SUNTRUST BANK
7	259518	NATIONAL CITY BANK
8	504713	U.S. BANK
9	485559	FIRST TN BANK
10	852320	BRANCH BKG&TC

Appendix for chapter 2

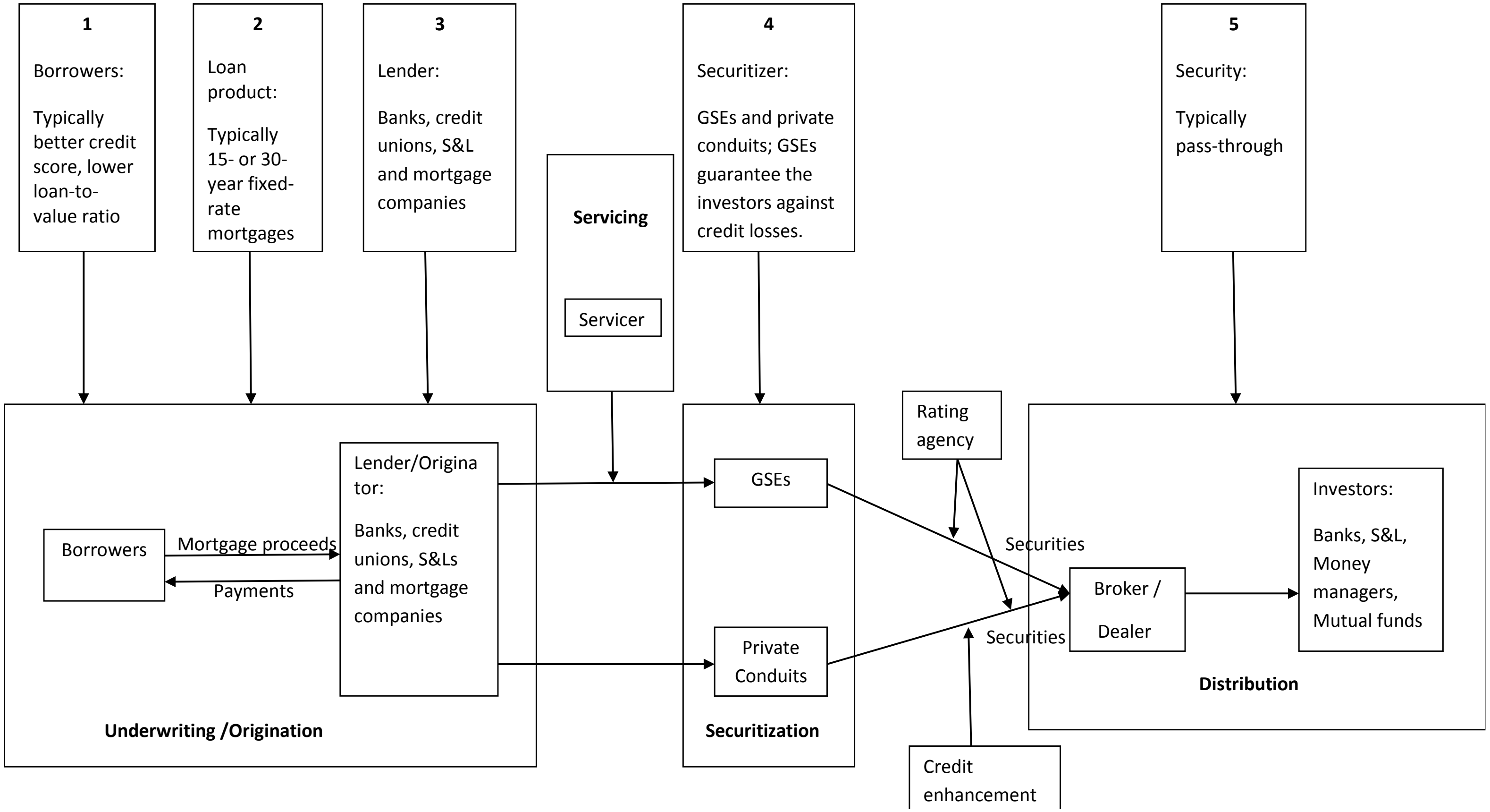

Figure A2.1: Securitization Process – The Prime Market

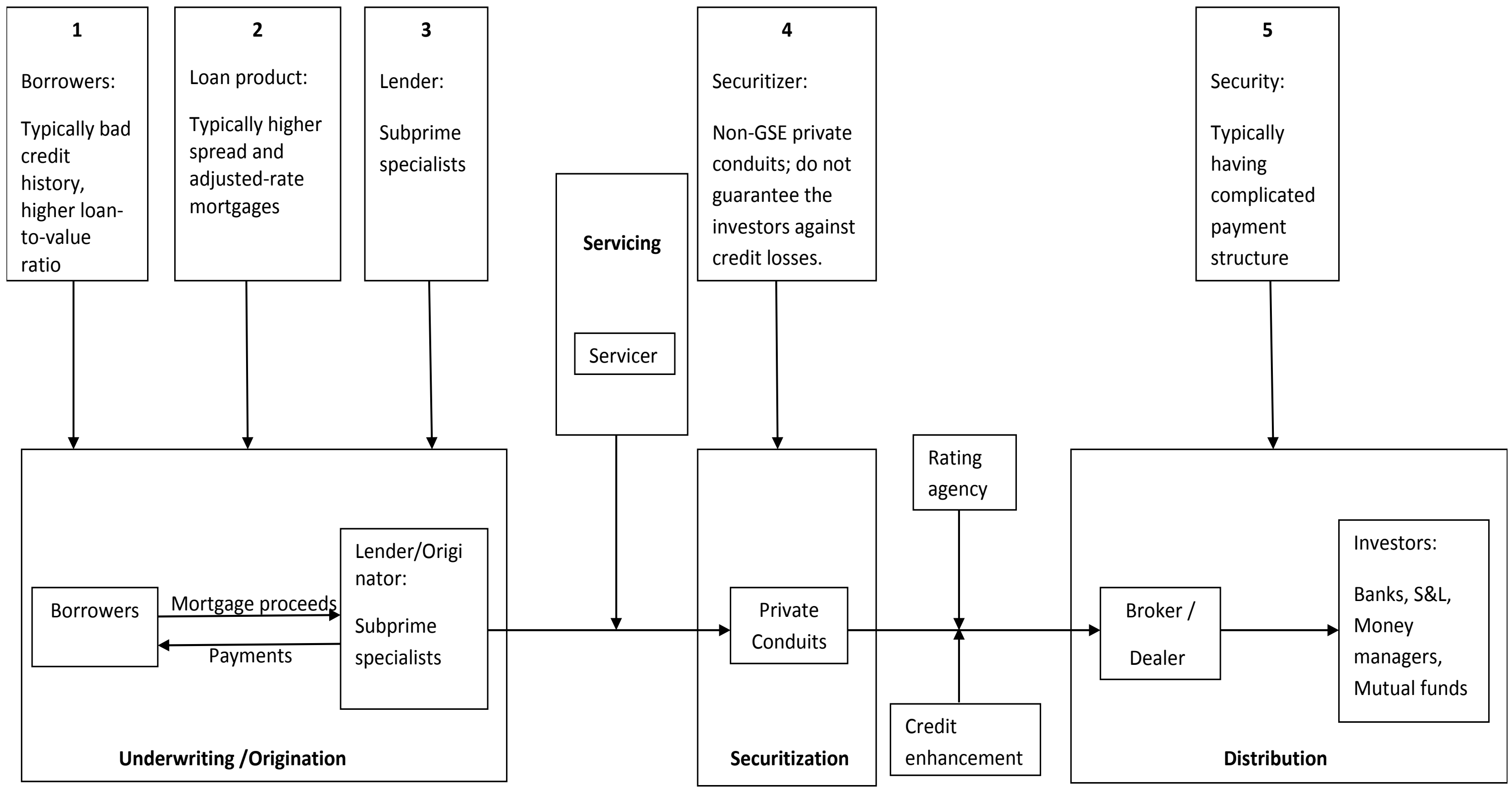

Figure A2.2: Securitization Process – The Subprime Market