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Liquidity Shocks and the
US Housing Credit Crisis of
2007–2008

Gianni La Cava

RDP 2013-05

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Abstract

There is extensive anecdotal evidence to suggest that a significant tightening in credit conditions, or a ‘credit crunch’, occurred in the United States following the collapse of the loan securitisation market in 2007. However, there has been surprisingly little formal testing for the existence of a credit crunch in the context of the US housing market. In this paper I examine whether the fall in mortgage credit over 2007–2008 was caused by a reduction in credit supply which, in turn, can be traced to a fall in the amount of financing available to mortgage lenders. I use the differential exposures of individual mortgage lenders to the collapse of the securitisation market in 2007 as a source of cross-lender variation in lender financing conditions and assess the impact on residential mortgage lending.

Using loan-level information to control for unobservable credit demand shocks, I show that mortgage lenders that were particularly reliant on loan securitisation disproportionately reduced the supply of mortgage credit. The negative liquidity shock caused by the shutdown of the securitisation market explains a significant share of the aggregate decline in mortgage credit during the crisis.

JEL Classification Numbers: C36, E21, G11, G12

Keywords: bank liquidity, credit supply, mortgage market, housing

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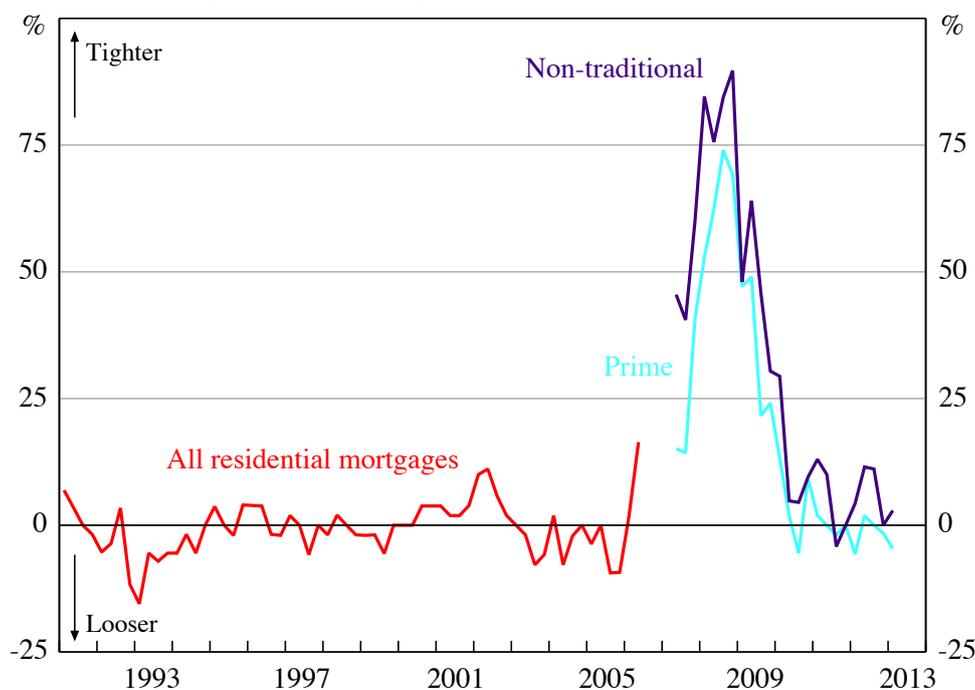
Liquidity Shocks and the US Housing Credit Crisis of 2007–2008

Gianni La Cava

1. Introduction

There is extensive anecdotal evidence to suggest that a significant tightening in credit conditions, or a ‘credit crunch’, occurred in the US housing market following the collapse of the loan securitisation market in late 2007. For example, the Federal Reserve’s Senior Loan Officer Opinion Survey indicates that the number of US banks that tightened lending standards rose sharply for both prime and subprime mortgages in the December quarter 2007 (Figure 1). The term ‘credit crunch’ has become so commonplace that the *Economist* magazine has created a Credit Crunch board game and the term is now officially part of the English language, having been recently included in the *Concise Oxford English Dictionary*.

Figure 1: Credit Standards for US Residential Mortgages
Net percentage reporting tightening standards



Source: Thomson Reuters

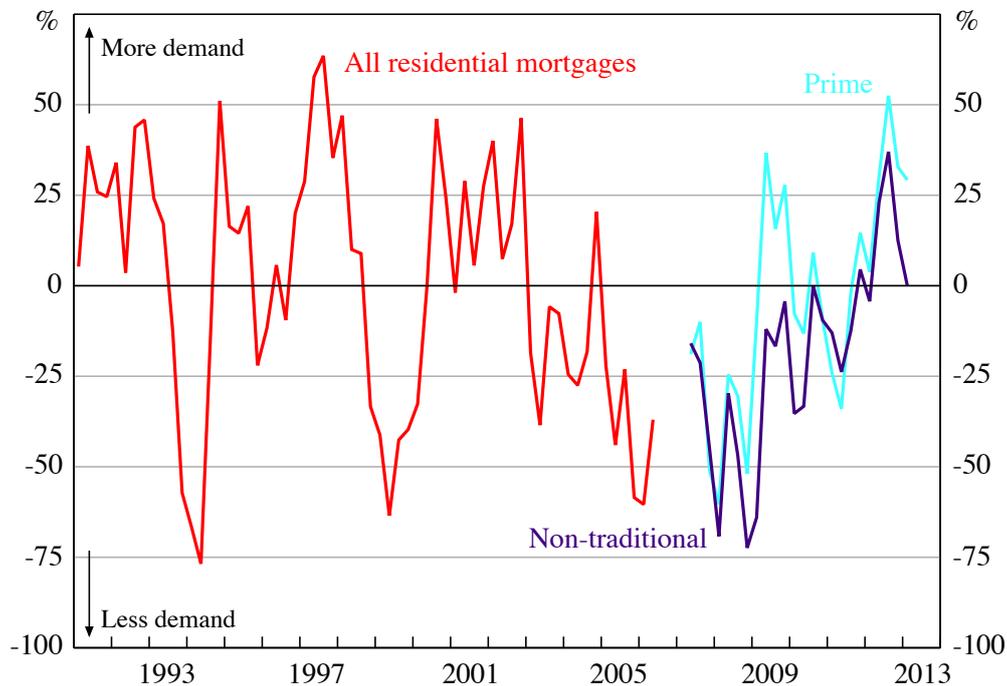
Despite its popularity as a concept, there has been surprisingly little formal testing of whether a credit crunch, in fact, occurred in the US housing market in 2007–2008. This is probably because the necessary conditions to test the hypothesis are quite strict. The most generally accepted definition of a credit crunch is attributable to Bernanke and Lown (1991) who define it as a ‘significant leftward shift in the supply curve for bank loans, holding constant both the safe real interest rate and the quality of potential borrowers’ (p 207). This definition requires two key conditions to be satisfied to establish a credit crunch: first, there should be a fall in credit that is caused by a decline in credit supply rather than demand; and, second, the fall in credit supply must be exogenous in the sense that it is not caused by an increase in the credit risk of potential borrowers. In other words, the fall in credit supply will generally be caused by factors affecting the size and composition of financial institutions’ balance sheets, such as a tightening in financing conditions.¹

The other reason why there has been little formal testing for a credit crunch is that it is difficult to conduct adequate econometric tests. There are two common econometric problems in identifying a credit crunch. First, a crunch typically coincides with a general decline in economic activity, which also causes the demand for credit to fall (simultaneity bias). Second, even if the decline in credit can be traced to a fall in supply, this may be an endogenous response by lenders to a decline in the quality of potential borrowers associated with the economic downturn (selection bias). The difficulty in separately identifying the effects of changes in credit supply and demand is highlighted by the Federal Reserve’s Senior Loan Officer Survey, which shows that the demand for mortgage credit also fell sharply around 2007–2008 (Figure 2). It is therefore possible that this decline in demand drove the overall fall in lending rather than a decrease in credit supply.

This paper tests whether the fall in mortgage credit over 2007–2008 was caused by a reduction in credit supply that, in turn, can be traced to a fall in the level of financing available to US mortgage lenders, which caused them to become liquidity constrained. I will refer to this as the ‘liquidity constraints hypothesis’. I use application-level information on new mortgage loans to assess how US

1 It is effectively a leftward shift of the credit supply curve where the quantity of credit is measured on the x-axis and the loan interest spread is measured on the y-axis.

Figure 2: US Residential Mortgage Demand
Net percentage reporting increased demand



Source: Thomson Reuters

mortgage lenders' lending behaviour changed as a result of the tightening in financing conditions.

In the first part, I estimate a model that identifies the liquidity shock based on each mortgage lender's reliance on securitised lending in the period prior to 2007. In this framework, the closure of the securitisation market acts as the 'treatment', the 'treatment group' are the mortgage lenders that were reliant on securitisation before 2007 and the 'control group' are the mortgage lenders that were not dependent on securitisation. I will refer to the treated lenders (those reliant on securitised lending) as the originate-to-distribute (or OTD) lenders, and the control group of lenders, which were not dependent on securitised lending, as the non-OTD lenders.

The novel aspect of this study is that the causal effect of the liquidity shock on mortgage lending is identified through variation in the lending activity of OTD and non-OTD lenders that grant credit to the *same* borrower (where a particular region is broadly defined as a 'borrower'). Specifically, I assume that mortgage lenders that originate loans in the same Census tract (a tract is similar to a postcode) face the same demand conditions and the same risk profile of loan applicants. Under

this assumption, a reduction in credit by OTD lenders relative to non-OTD lenders *within a tract* implies that a negative lender liquidity shock, and hence a decline in credit supply, caused the overall fall in mortgage credit.

I find strong evidence to indicate that the OTD lenders disproportionately reduced mortgage credit supply following the liquidity shock. The negative liquidity shock caused by the shutdown of the securitisation market explains about 14 per cent of the average decline in mortgage credit during the crisis. Moreover, I find that the link between lender funding liquidity and mortgage lending holds even after controlling for unobservable lender characteristics, such as changes in banks' assessment of borrowers' risks.

I also examine which borrowers were most affected by the reduction in credit supply due to the tightening in lender financing conditions. Theory suggests that lenders re-balance their portfolios towards less risky loans when economic conditions deteriorate (Bernanke, Gertler and Gilchrist 1996). During recessions, the share of credit flowing to borrowers with more severe asymmetric information and agency problems, such as small firms, decreases. This 'flight to quality' has been identified in a range of empirical studies (e.g. Lang and Nakamura 1995; Popov and Udell 2010). However, more recent research indicates that there may also be a 'flight to home' effect when economic conditions deteriorate (e.g. De Haas and Van Horen 2012; Giannetti and Laeven 2012). Specifically, lenders re-balance their asset portfolios towards local borrowers when the economy weakens, as lenders are typically better informed about local borrowers than non-local borrowers. The flight to home effect co-exists with, but is distinct from, the flight to quality effect. To the best of my knowledge, this paper is the first to examine whether the flight to quality and flight to home effects are relevant to residential mortgage lending.

I find that all mortgage lenders reduced credit to risky borrowers, though the effect was not disproportionately larger for the OTD lenders. This points to a general flight to quality by US mortgage lenders during the crisis. I find limited evidence for a flight to home caused by the liquidity shock; while the OTD lenders increased the share of credit to local borrowers relative to the non-OTD lenders, the differential effect is not significant.

2. Institutional Background

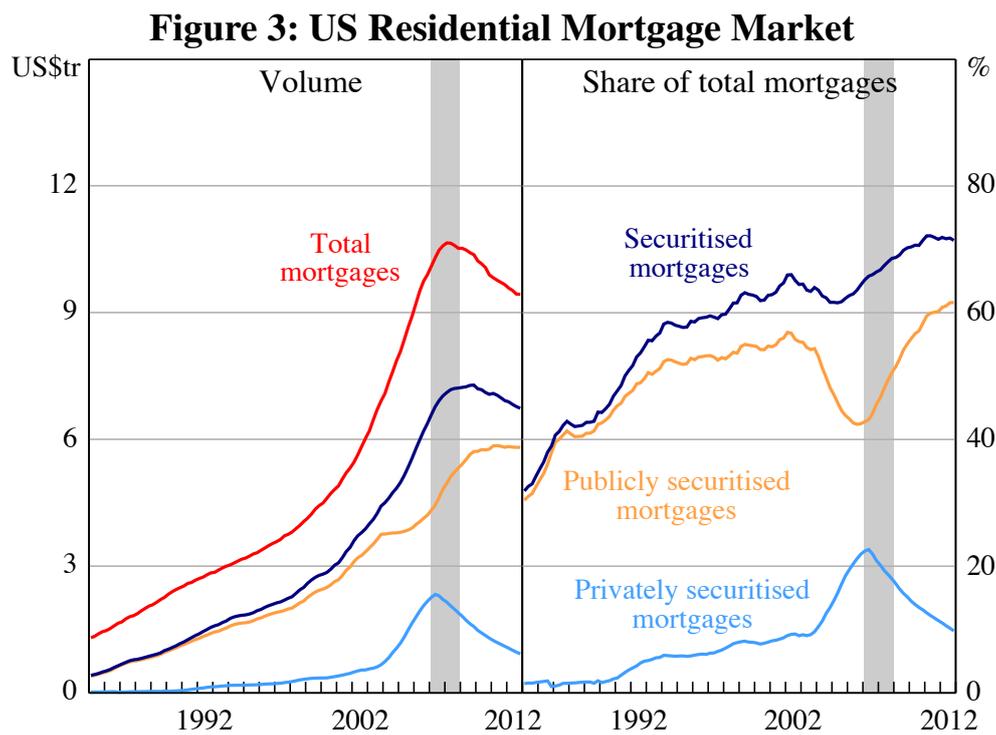
Mortgage securitisation refers to the process of pooling mortgages into securities that are then sold to investors on a secondary market. The securities are backed by the cash flow generated by the borrowers' mortgage payments. Securitisation is essentially a process that allows a loan originator to transform cash flows from a pool of non-tradable assets into tradable debt instruments. In doing so, securitisation provides financial institutions with an additional method of financing mortgages – in this case, through the issuance of mortgage-backed bonds rather than unsecured bonds or deposits.

Securitized bonds backed by home mortgages are known as 'residential mortgage-backed securities' (RMBS). In the United States, the RMBS market can be divided into two sectors: agency and non-agency (or private-label) RMBS. The agency market includes mortgages securitized by government-sponsored enterprises (GSEs), such as the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac). The GSEs have traditionally been private corporations with a public charter, operating with the implicit backing of the US Government. They have purchased residential mortgage loans on the secondary market from loan originators (e.g. banks) and then packaged these loans into securities, which they either sell to other investors or hold in their own portfolios. In this paper, I will sometimes refer to the loans securitized by the GSEs as 'public securitisations'. In contrast, the non-agency market comprises mortgages securitized by private financial institutions, such as commercial and investment banks. I will refer to these securitized loans as 'private securitisations'.

Loans that are securitized by the GSEs must meet certain eligibility criteria, based on factors such as loan size and other underwriting guidelines. Residential mortgages that are eligible to be purchased by the GSEs are known as 'conforming mortgages'. Mortgages that are non-conforming because their size exceeds the purchasing limit are known as 'jumbo' mortgages. Mortgages that are non-conforming because they do not meet other underwriting guidelines, such as credit quality, are often called 'subprime' mortgages. The private securitisation market

developed to facilitate the sale of mortgages that did not meet the GSEs' eligibility criteria.²

According to US flow of funds data, around 65 per cent of residential mortgages had been securitised at the time of the crisis (Figure 3). The bulk of these loans were securitised by the GSEs. However, the most recent housing cycle in the United States caused significant changes in the composition of US securitised home mortgage debt. The share of mortgages that were privately securitised rose rapidly around 2004–2006, coinciding with the boom in the US housing market. The increase in the share of private securitisations is likely to reflect several factors, such as an increase in demand for non-conforming mortgages by borrowers, an increase in demand for non-conforming mortgage securities by private investors, and a relaxation of lending standards by mortgage originators (Nadauld and Sherlund 2009).



Note: Shaded areas denote crisis period (2007–2008)

Source: Board of Governors of the Federal Reserve System

² Historically, the conforming mortgage loan limit has been periodically adjusted in line with changes in average US home prices. Higher limits apply for mortgages secured by homes that are: (i) located in high-cost housing areas, (ii) multi-family dwellings, and (iii) located in Alaska, Hawaii, Guam and the US Virgin Islands.

The share of private securitisations fell dramatically when the subprime mortgage market collapsed in the first half of 2007. The private securitisation market was effectively shut down by late 2007. In contrast, the public securitisation market continued to function due to implicit government backing and, eventually, explicit guarantees by the US Federal Reserve and US Treasury. This substitution away from private securitised lending to public securitised lending during the crisis suggests that the GSEs were able in part to step into the breach caused by the evaporation of the private-label market. This substitution could be important in identifying the effect of a liquidity shock on lending and will be discussed in a robustness test later.

Home mortgage lenders that are reliant on loan securitisation to fund the origination of new loans are often referred to as ‘originate-to-distribute’ (or OTD) lenders (Purnanandam 2011). The mortgage lenders that, instead, rely on other forms of funding, such as retail deposits, to originate loans are known as ‘originate-to-hold’ (or non-OTD) lenders. The non-OTD lenders retain, rather than sell, most of the loans on their balance sheets. This distinction between the two groups of lenders – the OTD and non-OTD lenders – is important in this study. I assume that the OTD lenders were more affected by the disruption to the securitisation market in 2007 than the non-OTD lenders. The distinction, therefore, provides a way to identify the effect of the liquidity shock stemming from the securitisation market. As the OTD lenders were highly dependent on securitisation to finance new lending, these lenders would have become relatively more liquidity constrained when investors withdrew funding from the secondary market.

3. Literature Review

In examining the relationship between bank liquidity and lending, this paper relates to several branches of the macroeconomic literature. The theoretical literature provides a framework in which banks’ financing conditions can affect overall lending due to credit market imperfections (e.g. Bernanke and Blinder 1988; Holmstrom and Tirole 1997; Stein 1998). But empirical studies face a challenge in tracing the channels through which credit supply shocks are transmitted. Traditionally, empirical research has relied on either time series or cross-sectional variation in the balance sheet positions of banks to identify

the effect of bank financing conditions on lending.³ For example, Peek and Rosengren (1995) use US bank-level data to document a positive relationship between bank capital and credit growth during the 1990–1991 recession. However, the evidence is not compelling, as banks that face more creditworthy borrowers are likely to experience fewer loan losses. The lower losses could translate into higher levels of capital and may also encourage more lending.⁴ In other words, endogeneity could be a problem because differences in bank-level credit growth may reflect differences in the risk profile of borrowers or other demand conditions. Other studies that use instrumental variables (Paravisini 2008) or natural experiments (Peek and Rosengren 2000) generally provide more compelling evidence that liquidity supply shocks, which are exogenous to demand, affect lending. For instance, Peek and Rosengren (2000) demonstrate that US subsidiaries of Japanese banks were more likely than domestic US banks to cut credit to the US commercial real estate sector following a negative balance sheet shock to their Japanese parent. As the shock stemmed from overseas, it is likely to have been exogenous to demand conditions in the United States. However, it is still possible that the Japanese subsidiaries and the domestic US banks were lending to different pools of borrowers within the US commercial real estate sector, so that differences in demand conditions across banks could still have driven the results.

My paper belongs to a growing literature that uses loan-level information to identify the causal effect of credit supply shocks. The increasing availability of loan-level data has allowed researchers to implement more sophisticated identification strategies than empirical studies that rely on either aggregate or bank-level data. The seminal paper in this branch of the literature is Khwaja and Mian (2008). They examine the impact of liquidity shocks on bank lending by exploiting cross-bank liquidity variation induced by unanticipated nuclear tests in Pakistan in 1998. The nuclear tests caused the Pakistani Government (in

3 There is a close analog to the literature on the credit channel of monetary policy. The credit channel of monetary policy can be divided into two channels – the ‘bank lending channel’ and the ‘borrower balance sheet channel’. The bank lending channel measures the effect of monetary policy shocks on the real economy through their effect on the balance sheets of lenders. In contrast, the borrower balance sheet channel measures the effect of monetary policy shocks on the real economy through their effect on borrower balance sheets. The effect of liquidity shocks on lending is sometimes loosely referred to as a ‘bank lending channel’ in the literature, despite the fact that neither monetary policy nor the real economy are considered.

4 Lower loan losses will also indirectly boost the level of lending, as the existing stock of loans will not be dragged down by loans that are written off.

anticipation of balance of payment problems) to restrict withdrawals of US dollar-denominated deposit accounts to local currency only, and at an unfavourable exchange rate. The collapse of the US dollar-denominated deposit market disproportionately affected banks that relied more on US dollar-denominated deposits for liquidity. They show that, for the same firm borrowing from two different banks, the bank exposed to the larger potential decline in liquidity was more likely to reduce lending. To the extent that the within borrower comparison fully absorbs borrower-specific changes in credit demand, the estimated difference in loan growth between banks can be attributed to differences in bank liquidity shocks. This within borrower identification scheme has now been adopted in a range of empirical studies that have access to loan-level information (e.g. Albertazzi and Marchetti 2010; Iyer *et al* 2010; Jimenez *et al* 2011; Cetorelli and Goldberg 2012; Schnabl 2012). To the best of my knowledge, this paper is the first to apply this within borrower identification strategy to household lending.

The US housing credit market provides a natural testing ground to examine the nature of credit supply shocks because it was the market at the epicentre of the global financial crisis. Most of the existing research on the current crisis has looked at the effect of changes in credit supply on the investment behaviour of large corporate borrowers (e.g. Duchin, Ozbas and Sensoy 2010; Ivashina and Scharfstein 2010; Campello *et al* 2012). But this is unlikely to be the primary channel through which the financial crisis affected the real economy. Instead, the prolonged period of weak economic conditions in the US economy was more likely to be due to developments in residential mortgage finance.

There are a few other recent papers that also treat the shutdown of the securitisation market in 2007 as a negative liquidity shock and examine how this affected bank lending (e.g. Gozzi and Goetz 2010; Calem, Covas and Wu 2011; Dagher and Kazimov 2012). However, my paper covers a wider cross-section of lenders, a longer time series, and utilises loan-level information which allows me to control for variation in the distribution of borrowers across banks more effectively.

Gozzi and Goetz (2010) focus on small banks that lend within their own local markets while I examine the behaviour of all lenders, regardless of size, location or geographic reach. Restricting the sample to small local banks is likely to bias the causal effect of bank liquidity shocks for two reasons. First, if affected borrowers are able to switch to large banks when small banks cut off their funding then

restricting the sample to only small banks may overstate the true aggregate effect of the shock. Second, if liquidity-constrained banks are relatively more likely to cut lending to non-local borrowers, then the focus on local lending could understate the true effect of a credit supply shock.

Calem *et al* (2011) rely on bank-level variation in funding liquidity and lending and hence only control for unobservable variation in the characteristics of each bank's average borrower. In contrast, I control for changes in the distribution of each bank's (unobservable) borrower characteristics. This will be important if the effect of the supply shock varies across different borrowers within a bank's loan portfolio.

Dagher and Kazimov (2012) also treat the shutdown of the securitisation market as an exogenous negative liquidity shock, but use each bank's share of non-deposit funding, rather than the share of securitisation funding, to identify the treatment group of mortgage lenders. Their identification strategy also assumes that loan applicants that reside within the same metropolitan statistical area share similar characteristics, whereas my strategy assumes that applicants residing in the same Census tract are similar, which is more likely to be true given that tracts are defined based on residents sharing similar characteristics. And, unlike my study, Dagher and Kazimov do not consider which borrowers were most affected by the credit supply shock.⁵

The housing market is also a potentially interesting area in which to identify any home bias in lending because the location of the asset (the home) is a fundamental determinant of its price (and hence its collateral risk). Geographic location is therefore potentially a significant determinant of credit risk in home mortgage lending. There is an extensive literature identifying a home bias in the global allocation of capital (Coeurdacier and Rey 2011) but, to the best of my knowledge, there is little research on home bias in residential mortgage lending.

⁵ According to US flow of funds data, the outstanding value of RMBS (US\$6.4 trillion) was twice as large as the outstanding value of non-deposit liabilities owed by private depository institutions (US\$3.2 trillion) at the end of 2006. Moreover, the flow of funds indicates that the stock of non-deposit funding continued to grow during the crisis period, while data provided by the Securities Industry and Financial Markets Association (SIFMA) suggest that RMBS issuance fell by about US\$1 trillion between 2006 and 2008. This suggests that the shock to the RMBS market was more likely to have had a significant impact on US bank liquidity, and hence mortgage lending, than any shock to non-deposit funding.

Moreover, only recently has evidence emerged that this home bias increases when economic conditions worsen (i.e. that there is a flight to home effect). For example, in response to an adverse shock to financing conditions, international banks in the syndicated lending market shifted their lending activity towards their home country, regardless of the perceived risk of the borrowers (Giannetti and Laeven 2012; De Haas and Van Horen 2012). Broadly speaking, there are two possible explanations for a home bias in credit markets – information asymmetries and behavioural biases. If lenders cannot observe borrower risk perfectly and it is costly to collect information on the creditworthiness of borrowers then lenders may be better informed about local borrowers than non-local borrowers. Under this explanation, geographic distance is a proxy for credit risk and, similar to the flight to quality, lenders will re-balance their portfolios towards local borrowers when economic and financial conditions deteriorate. Alternatively, certain lenders may specialise in lending to distant borrowers and have more sophisticated loan screening and monitoring technologies than local lenders. In this case, local lenders would not have an informational advantage, so any home bias may be better explained by a behavioural bias towards familiar assets rather than by information asymmetries.

4. Data

4.1 The Home Mortgage Disclosure Act

The data underpinning the regression analysis are derived from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. Enacted by Congress in 1975, HMDA requires mortgage lenders located in metropolitan areas to collect data about their housing-related lending activity and make these data publicly available. The HMDA dataset is generally considered to be the most comprehensive source of mortgage data in the United States, and covers about 80 per cent of all home loans nationwide and a higher share of loans originated in metropolitan statistical areas. Whether a lender is covered depends on its size, the extent of its activity in a metropolitan statistical area, and the weight of residential mortgage lending in its portfolio.

The underlying sample of mortgage loan applications includes almost 300 million annual observations covering the period 2000–2010. For each application there is information on the loan application (e.g. the type of loan, the size of the loan,

whether the loan is approved or not), the borrower (e.g. income, race, ethnicity), and the lending institution (e.g. the identity of the lender).⁶ Most importantly for the purposes of this paper, I can identify whether a loan is sold to another financial institution or not. I assume that loan sales and loan securitisations are equivalent, so that I can directly observe the extent of securitisation activity by each mortgage lender.⁷ I can also identify the type of institution that purchased the loan, which allows me to split loan securitisations into private and public securitisations. In particular, I identify public securitisations as any loans that were sold to the GSEs. I classify the remaining loan sales as private securitisations.

The raw loan application data are not panel data as the behaviour of specific borrowers cannot be tracked over time, although a given lender can be observed each year. To create a pseudo-panel I aggregate the annual loan application data so that the data vary by lender and Census tract. This means that I track the lending of a given loan originator to the *average* borrower in a given Census tract across time. A Census tract is a very narrowly defined geographic region. The tracts are designed, for the purpose of taking the Census, to be relatively homogeneous units in terms of population characteristics, economic status, and living conditions. In the United States, there are about 73 000 Census tracts, and each tract has between 2 500 and 8 000 residents. Several tracts commonly exist within a county, with the boundaries of a tract usually coinciding with the limits of cities and towns. The very narrow geographic focus of Census tracts supports my identification strategy, as different borrowers in the same tract are likely to share similar characteristics. This ensures that two different lenders that originate loans in the same tract are likely to face the same demand conditions and borrower risk profiles.

The HMDA dataset covers bank and non-bank lenders (i.e. mortgage companies). The non-bank lenders are an important segment of the US mortgage market. Over the sample period, they originated more than half of all new residential mortgage

6 I restrict the sample to conventional owner-occupier one-to-four family residential mortgages, which is consistent with numerous other studies.

7 Loan sales and securitisations are separate but closely related concepts. A loan sale involves the lender selling the loan in its entirety to another institution. If that institution wants to sell it again, they have to find a buyer and negotiate a price. A loan securitisation involves the lender selling a loan (or portfolio of loans) to investors where the loan (or portfolio) is converted into rated securities, which are publicly traded. In general, loan sales are a broader measure of financing lending than securitisations.

loans. Moreover, with no access to depository funding, non-bank lenders typically operate under the originate-to-distribute (OTD) business model and hence are much more reliant on loan securitisation for funding. The market share of these lenders typically varies with the credit cycle, so including these non-bank lenders in the sample reduces the probability of sample selection bias in identifying the effect of financing conditions on credit supply.

4.2 Measuring Mortgage Lending and Bank Liquidity

As will be discussed in the next section, in the main regression model, the dependent variable is a measure of the change in lending activity by each mortgage lender in each tract during the crisis. My preferred measure of lending activity is the number of new loans.⁸ I proxy the liquidity shock through the average propensity of each mortgage lender to securitise loans in the pre-crisis period. More specifically, for each lender and each year, I calculate the ratio of the number of new loans that are sold to the total number of new loans and then, for each mortgage lender, average across all the years of the pre-crisis period. This averaging process is partly aimed at transforming the flow of loan sales into an approximate measure of each lender's stock of loan sales in the pre-crisis period, as the stock determines each lender's exposure to the liquidity shock.⁹ I define the pre-crisis period to be 2000 to 2006. However, the results are not sensitive to the length of the pre-crisis period. For example, similar results are obtained when the pre-crisis period is defined as 2004 to 2006.

My set of control variables includes lender-tract controls, such as the average growth in income of the borrowing household and the share of minority household applicants faced by each lender in each tract, as well as lender-level controls, such as the average (log) number of loan applications, which acts as a proxy for lender size.¹⁰ I exclude other lender-level variables, such as measures of profitability, as these data are unavailable for non-bank lenders. The non-bank lenders are

8 I have also estimated the regressions using alternative measures of lending activity, such as the total value of new loans and the share of applications that are approved. The results are qualitatively very similar.

9 The averaging process also smoothes the data and minimises any 'lumpiness' in RMBS transactions by financial institutions.

10 I define minority households as all African-American or hispanic households.

an important segment of the US mortgage market and could be critical to the relationship between loan securitisation and credit supply given they typically operate under the OTD business model.

The second part of the analysis relies on a measure of borrower risk to test the flight to quality hypothesis. I measure the borrower risk faced by each lender through the share of high-priced loans originated by each lender in each tract. Information on the interest rate spread was added to the HMDA dataset in 2004. However, HMDA respondents are only required to report the interest rate spread on a subset of loans. Mortgages with a reported spread are ‘higher-priced’ loans.¹¹ As the interest rate spread on a loan largely reflects the credit risk of a borrower, the share of high-priced mortgages is often viewed as an indicator of risky or subprime lending (Mayer and Pence 2008). This measure of risky lending is only available since 2004, so this necessarily restricts the time series available to establish the pre-crisis period in the second part of the analysis.¹²

To test the flight to home hypothesis I construct a measure of each bank’s average lending distance based on the detailed information provided by the HMDA. The HMDA dataset includes information on the Census tract of the residence of each loan applicant, as well as the full address details of the headquarters of each mortgage lender. This allows me to estimate the geographic distance between each borrower and lender using geocoding software provided by STATA and Google Maps. I then calculate, for each lender in each year, the average distance across all its borrowers within a given Census tract, which provides a measure of ‘lending distance’ at the lender-tract level.

The set-up of the regression model implies that the sample is restricted to tracts in which there is at least one OTD lender and one non-OTD lender originating new

11 Higher-priced loans are those with an interest rate spread to the comparable-maturity Treasury for first-lien mortgages with an annual percentage rate (APR) 3 percentage points over the Treasury benchmark and for junior liens with an APR 5 percentage points over the benchmark. A lien is the legal claim of the lender upon the property for the purpose of securing debt repayments. The lien given the highest priority for repayment is the first lien; any other liens are junior liens. Because junior liens are less likely to be repaid, they are a higher risk to the lender than the first lien. In the US mortgage market, junior liens can include home equity loans and home equity lines of credit.

12 There are at least two problems with using the share of high-priced loans as an indicator of risky or subprime lending. I talk about these issues in more detail in Appendix D.

loans. In other words, I exclude tracts in which there is only one type of lender. The final sample comprises about 5 000 mortgage lenders that lend to more than 60 000 tracts in the United States. Table 1 provides summary statistics for the key variables used in the panel regression.

Table 1: Variable Summary Statistics

Variable	Mean	Median	25th pct	75th pct	Std dev
<i>Pre-crisis, 2000–2006</i>					
Sale share (%)	36.1	14.3	0.0	80.2	40.5
Private sale share (%)	29.6	1.8	0.0	63.5	39.1
Public sale share (%)	6.5	0.0	0.0	0.4	17.6
Minority ratio (%)	12.0	0.0	0.0	13.3	22.7
No of applications (log level)	4.7	4.7	3.4	6.0	2.2
<i>Post-crisis, 2007–2008</i>					
No of loans (% change)	−18.7	−2.4	−67.2	14.4	66.7
Household income (% change)	7.1	6.8	−17.6	31.1	48.6

Source: Home Mortgage Disclosure Act Loan Applications Registry

The summary statistics show that, on average, 36.1 per cent of all approved loans were sold in the pre-crisis period (2000–2006) and that 12.0 per cent of household loan applicants were from a minority group.¹³ Moreover, the number of new loans fell by 18.7 per cent over the crisis period (2007–2008) while average household income rose by 7.1 per cent, on average.

5. Testing the Liquidity Constraints Hypothesis

5.1 Identification

I estimate a difference-in-differences panel regression model to examine the causal effect of bank liquidity shocks on mortgage lending. The set-up of the model is based on an experimental design in which there are two groups of lenders – a

¹³ The estimated share of loan sales in the HMDA data (36 per cent) is significantly lower than the share of loan securitisations suggested by the US flow of funds (63 per cent) over the corresponding period. This is mainly because the flow of funds estimate is based on aggregate mortgage data while the HMDA estimate is based on bank-level mortgage data. The different estimates reflect the distribution of loan sales across lenders of different sizes. There is a large number of small banks in the United States that sell few loans, which implies that the bank-level mean estimate is lower than the aggregate estimate. Aggregating the HMDA data to the national level, the share of loans sold is about 60 per cent, which is similar to the flow of funds estimate.

‘treatment group’ (the OTD lenders) and a ‘control group’ (the non-OTD lenders) – as well as a ‘treatment’ (the closure of the securitisation market in 2007). I first write the regression model in terms of levels:

$$L_{ijt} = \alpha + SALES\text{SHARE}'_i\beta + CRISIS'_t\gamma + SALES\text{SHARE}'_i * CRISIS'_t\rho + X'_{ijt}\phi + \underbrace{\theta_j + \eta_{jt} + \varepsilon_{ijt}}_{v_{ijt}} \quad (1)$$

where the dependent variable is the (log) number of new loans of lender i to tract j in period t (L_{ijt}). The explanatory variables include the share of loans that were sold by lender i in the pre-crisis period ($SALES\text{SHARE}'_i$), a dummy variable for whether the period is pre- or post-crisis ($CRISIS'_t$) and an interaction variable ($SALES\text{SHARE}'_i * CRISIS'_t$). I also include a set of control variables (X_{ijt}) that vary by lender, tract and time, such as the average income of loan applicants and the share of loan applicants that are from a minority group, as well as controls that vary by lender and time only, such as lender size. The composite error term (v_{ijt}) consists of a tract-specific effect (θ_j), a tract-specific time trend (η_{jt}) and an idiosyncratic term (ε_{ijt}). The tract-specific effect captures unobservable factors in each tract that do not vary with time (e.g. geographic factors) while the tract-specific time trend captures unobservable factors in each tract that do vary with time (e.g. local housing prices or employment prospects).

I collapse the time series information into two periods – the pre-shock (‘before’) and post-shock (‘after’) periods – by taking the average of all observations before and after the crisis. The pre-shock period covers the years 2000 to 2006 while the post-shock period covers the years 2007 to 2008. Difference-in-differences estimation that uses many periods of data and focuses on serially-correlated outcomes can produce inconsistent standard errors (Bertrand, Duflo and Mullainathan 2004). Collapsing the data in this way smoothes out variation and generates conservative standard errors.

To aid computation, I take the first difference over time between the pre- and post-crisis periods to obtain the equation in growth rates:

$$\Delta L_{ij} = \gamma + SALES\text{SHARE}'_i\rho + \Delta X'_{ij}\phi + \underbrace{\Delta\eta_j + \Delta\varepsilon_{ij}}_{\Delta v_{ij}} \quad (2)$$

where the dependent variable is the percentage change in the number of new mortgage loans by lender i to tract j between the pre- and post-crisis periods (ΔL_{ij}). The key explanatory variable is the share of loans sold by lender i on average in the pre-crisis period ($SALESHARE_i$). This variable is the proxy for the liquidity shock. The main coefficient of interest is the difference-in-differences estimator ($\hat{\rho}$) which measures the causal effect of the liquidity shock on mortgage lending during the crisis. The test of the liquidity constraints hypothesis is a test of whether mortgage lenders that were reliant on securitisation pre-crisis, and hence more exposed to the negative liquidity shock, reduced lending by more than mortgage lenders that were not reliant on securitisation (i.e. $\rho < 0$). The equation is reduced form in nature but can be derived as an equilibrium condition by explicitly modelling the credit supply and demand schedules (see Appendix A for the derivation).

The OLS estimator of ρ will be biased if unobservable credit demand shocks are correlated with a lender's reliance on loan sales (i.e. $corr(SALESHARE_i, \Delta\eta_j) \neq 0$). It is difficult to determine the direction of this bias. On the one hand, a lender's reliance on loan sales and the credit demand shocks could be positively correlated, which will lead to a positive OLS bias and the effect of the liquidity shock will be underestimated. For example, only lenders that experience particularly rapid growth in loan demand may turn to securitisation if it is relatively more expensive to fund a loan through securitisation than through retail deposits (e.g. due to deposit insurance). On the other hand, a lender's reliance on loan sales and the credit demand shocks could be negatively correlated, which will cause a negative OLS bias and the effect of the liquidity shock will be overestimated. For instance, OTD lenders might be more likely to lend to risky borrowers that became particularly discouraged from borrowing when economic conditions deteriorated. More generally, variation in borrower composition across OTD and non-OTD banks that directly affects credit demand biases the estimated coefficient on the loan sale share variable.

To address this issue, I include tract dummies ($\Delta\eta_j$) in the estimating equation that fully absorb all regional demand shocks, such as shocks to growth in local housing prices or local unemployment rates. The identification strategy assumes that changes in credit demand are felt proportionately across different banks that lend to borrowers *in the same tract*. The model then identifies the causal effect of

the liquidity shock through variation in the lending behaviour of OTD and non-OTD lenders within the same tract. The remaining identifying assumption is that the financial crisis was not anticipated, so that a lender's reliance on the secondary market and lender-tract shocks are uncorrelated (i.e. $\text{corr}(\text{SALESHARE}_i, \Delta \varepsilon_{ij}) = 0$). Put differently, US mortgage lenders did not adjust their financing structures in anticipation of the shock.

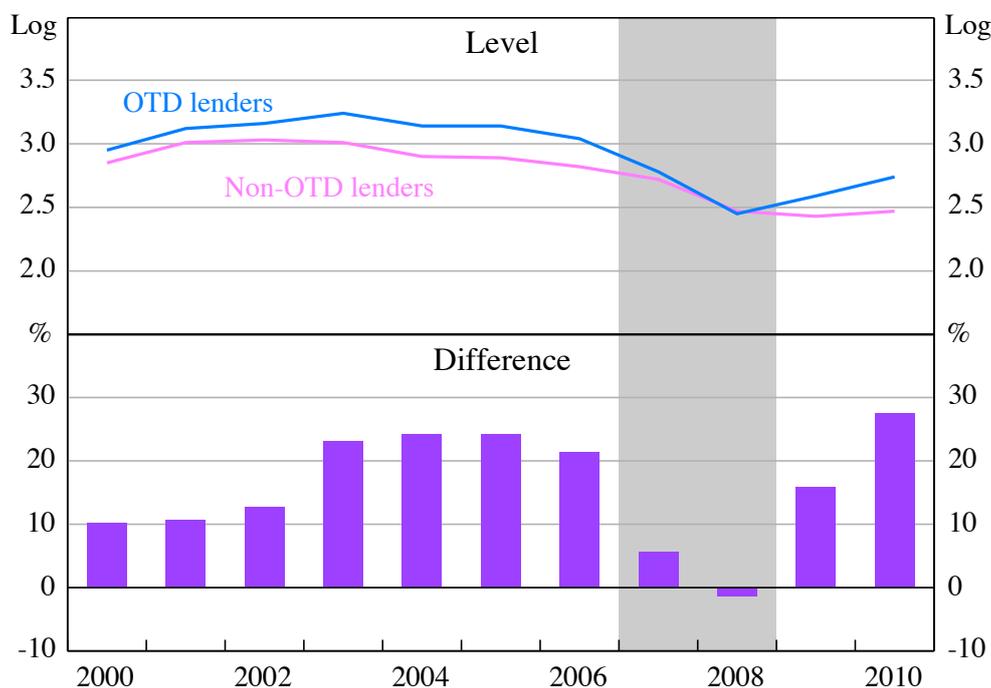
5.2 Graphical Analysis

Before turning to the econometric analysis it is instructive to inspect the trends in the disaggregated loan-level data that underpin the regression. The graphical analysis is designed to see whether the difference-in-differences regression is driven by appropriate identification assumptions. The key identifying assumption in my empirical strategy is that the trends in mortgage lending are the same for the OTD lenders and non-OTD lenders in the absence of the shock to the securitisation market. This is known as the common (or parallel) trends assumption. Specifically, I compare the trends in the mortgage lending of OTD and non-OTD lenders, both before and after the credit crisis.

To aid comparisons with the regression analysis, I construct *conditional* estimates of the lending of both types of lenders. Specifically, I split lenders into OTD and non-OTD lenders based on whether the share of loan sales is above or below the lender-mean each year. I then separately calculate the average level of lending for both OTD and non-OTD lenders each year, and plot the logarithm of this mean estimate over time.

The aggregate trends in Figure 4 illustrate the impact of the liquidity shock on lending and generally support the identification strategy. Prior to the crisis, the trends in average lending for the two types of lenders were very similar, with the gap in lending between the two groups being relatively constant over time. This constant gap in lending activity supports the common trends assumption. As the crisis hit, the OTD lenders reduced new lending by significantly more than the non-OTD lenders, particularly in 2008. As the US economy emerged from recession in 2009, the gap in lending between the two groups then reverted back to its pre-crisis level. This overall time series pattern of lending is consistent with the hypothesis that the OTD lenders became liquidity-constrained when a major source of funding – loan securitisation – declined sharply, and this caused them

Figure 4: New Mortgage Lending by Type of Lender
Conditional estimates



Note: Shaded areas denote crisis period (2007–2008)

Source: Home Mortgage Disclosure Act Loan Application Registry

to reduce credit supply relative to the non-OTD lenders that were not liquidity constrained.

5.3 Econometric Analysis

Table 2 summarises the results of estimating the benchmark difference-in-differences equation for the causal effect of the liquidity shock. The first column provides the OLS estimates as a benchmark and the second column provides the preferred tract fixed-effects estimates.

Overall, the results strongly support the hypothesis that the negative shock to lender financing conditions caused a reduction in mortgage credit supply. Each model specification suggests that mortgage lenders that were particularly reliant on loan securitisation cut lending by relatively more during the crisis. The estimates of the effect of the liquidity shock on the number of new loans are shown in the first row of the table. The fixed-effect estimate, which controls for unobservable trends in credit demand, is -0.077 (column 2) while the OLS estimate of the causal effect is -0.094 (column 1). The OLS estimate is further

from zero than the fixed-effects estimate, which suggests that the OLS bias is negative. The coefficient estimate from the fixed-effects specification implies that a one percentage point increase in the share of loans sold is associated with a decline in the level of new mortgage lending of about 7.7 per cent during the crisis. Alternatively, a one standard deviation increase in the share of loans that are sold (the standard deviation is 34 per cent) is associated with a fall in the level of new mortgage lending of about 2.7 per cent ($= -0.077 \times 0.34 \times 100$) during the crisis. At the lender-tract level, the total number of new loans fell by around 18.7 per cent, on average, over the crisis period. In other words, the estimates imply that a one standard deviation liquidity shock explains about 14 per cent ($= 2.7/18.7 \times 100$) of the total decline in new mortgage credit. This effect is economically meaningful.

The coefficient estimates on the control variables are statistically significant. The income growth of loan applicants is positively correlated with growth in the number of new loans over the crisis period. The share of loan applicants that are from a minority has a negative effect on lending activity during the crisis. Also, larger mortgage lenders, as measured by the average number of loan applications, cut lending by more than smaller lenders during the crisis.

Table 2: New Mortgage Lending

Variable	OLS (1)	Tract fixed effects (2)
Sale share	-0.0937*** (-2.74)	-0.0774** (-2.17)
Income growth	0.0719** (8.75)	0.0679*** (8.63)
Minority share	-0.0398** (-2.15)	-0.0840*** (-3.66)
Lender size	-0.0208*** (-3.22)	-0.0217*** (-3.14)
Constant	0.0824 (1.36)	0.0875 (1.31)
R^2	0.015	0.062
Observations	1 848 528	1 848 528

Notes: t statistics in parentheses; ***, ** and * indicate significance at the 1, 5 and 10 per cent level, respectively; standard errors are clustered at the lender and tract levels

6. Testing the Flight to Quality and Flight to Home Hypotheses

6.1 Identification

I now re-estimate the benchmark equation but augment it with indicators of borrower risk to determine how the effects of the liquidity shock vary across different classes of borrowers. I estimate the following panel regression model:

$$\begin{aligned} \Delta L_{ij} = & \alpha_0 + SUBPRIME'_{ij}\alpha_1 + DISTANCE'_{ij}\alpha_2 + SALESHARE'_i\beta_0 \\ & + SUBPRIME_{ij} * SALESHARE'_i\beta_1 + DISTANCE_{ij} \\ & * SALESHARE'_i\beta_2 + \Delta X'_{ij}\phi + \Delta \eta_j + \Delta \varepsilon_{ij} \end{aligned} \quad (3)$$

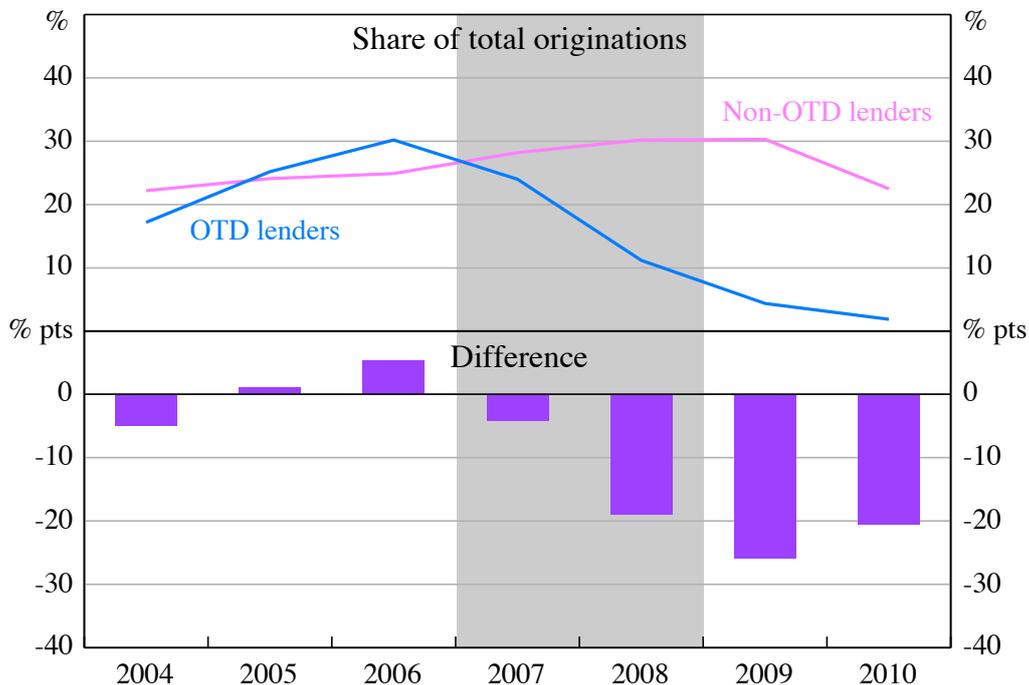
The dependent variable (ΔL_{ij}) is again a measure of the percentage change in lending activity during the crisis for lender i in tract j . Amongst the independent variables, I again include the liquidity shock variable ($SALESHARE_i$) but I now also interact this variable with indicators for whether the lending is risky or not and the distance between the borrower's home tract and the location of the lender's headquarters. More specifically, as explanatory variables I include a variable that measures the ratio of subprime lending to total lending ($SUBPRIME_{ij}$) of lender i in tract j and a measure of the (log) number of kilometres between the headquarters of lender i and tract j ($DISTANCE_{ij}$). I also include the same set of pre-crisis control variables (X_{ij}) as in the benchmark equation.

If the liquidity shock caused a flight to quality, the coefficient on the interaction variable $SUBPRIME * SALESHARE$ will be less than zero ($\beta_1 < 0$) as OTD lenders shift lending away from subprime borrowers by more than non-OTD lenders. If the liquidity shock caused a flight to home, the coefficient on the interaction term $DISTANCE * SALESHARE$ will be less than zero ($\beta_2 < 0$) as OTD lenders disproportionately reduce lending to distant borrowers. These hypotheses do not, however, rule out a more general flight to quality or flight to home by all lenders, but simply that these effects are not driven by the liquidity shock.

6.2 Graphical Analysis

Splitting lenders into the two groups – OTD and non-OTD lenders – within each tract and year, I now examine how different types of lending evolved. In Figure 5, I plot the evolution of the share of subprime lending for both OTD and non-OTD lenders. There is some evidence that the OTD lenders reduced their exposure to subprime lending by more than the non-OTD lenders around the time of the crisis. The overall share of subprime lending was broadly similar for the two groups in the pre-crisis period but a wedge emerged in 2007 as the subprime lending of the OTD lenders shrunk while the subprime lending of the non-OTD lenders remained elevated. The difference in the share of subprime lending persisted through the post-crisis period. This shift away from risky lending to less-risky lending is consistent with a flight to quality by the mortgage lenders most affected by the liquidity shock.

Figure 5: New Subprime Mortgage Originations
Conditional estimates



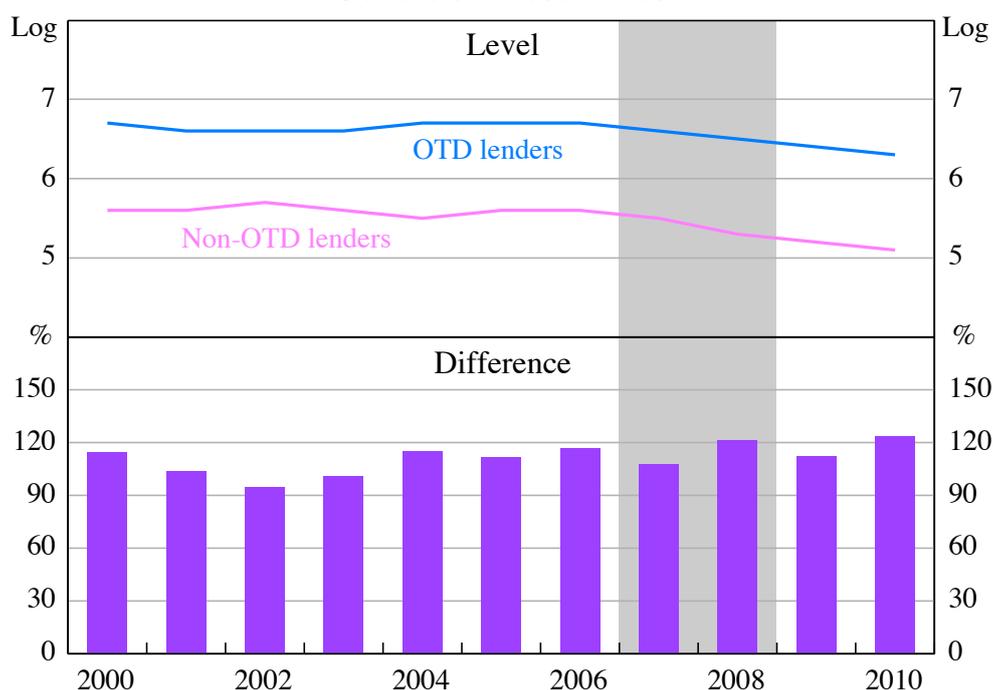
Note: Shaded areas denote crisis period (2007–2008)

Source: Home Mortgage Disclosure Act Loan Application Registry

In Figure 6, I plot the evolution of the average lending distance for both groups. There is little aggregate evidence that the OTD lenders shifted their mortgage lending towards borrowers that were closer to their head offices by more than the

non-OTD lenders. The conditional estimates indicate that, on average, the OTD lenders originate loans at more than twice the distance of non-OTD lenders. The average lending distance of the OTD lenders fell slightly relative to the non-OTD lenders in 2007, but quickly recovered the next year. In other words, based on this simple graphical analysis, there is little evidence in favour of the flight to home effect driven by the liquidity shock.

Figure 6: New Mortgage Lending Distance
Conditional estimates



Note: Shaded areas denote crisis period (2007–2008)

Sources: Home Mortgage Disclosure Act Loan Application Registry; author's calculations

6.3 Econometric Analysis

The liquidity shock stemming from the securitisation market had a sizeable negative impact on mortgage lending. Estimates of Equation (3) show which borrowers were most affected by the shock (Table 3).

The negative coefficient on the *SUBPRIME* variable indicates that there was a tendency for all lenders to reduce credit to subprime borrowers during the crisis. Moreover, the negative coefficient on the *SUBPRIME* * *SALESHARE* interaction variable suggests that OTD lenders cut lending to subprime borrowers by more than the non-OTD lenders. However, the differential effect is not statistically

significant. In other words, there is evidence that *all* lenders reduced credit to subprime borrowers, rather than just the OTD lenders, which is inconsistent with the specific flight to quality hypothesis considered here. The positive coefficient on the *DISTANCE* variable suggests, surprisingly, that there was a tendency to increase lending to more distant borrowers during the crisis, although the negative coefficient on the *DISTANCE* * *SALESHARE* interaction variable implies that the OTD lenders cut lending to more distant borrowers by more than the non-OTD lenders. However, the differential effect is, again, not statistically significant. In other words, there is limited evidence to support the flight to home hypothesis that the change in lending behaviour is caused by the liquidity shock.

Table 3: New Mortgage Lending by Type of Borrower

Variable	OLS (1)	Tract fixed effects (2)
Subprime	-0.364** (-2.31)	-0.429* (-2.70)
Distance	0.0211 (1.52)	0.0423* (2.86)
Sale share	-0.145*** (-1.75)	-0.0309 (-0.32)
Subprime x sale share	-0.279 (-1.25)	-0.227 (-0.99)
Distance x sale share	0.0102 (0.55)	-0.00345 (-0.16)
Income growth	0.0775* (7.62)	0.0725* (7.48)
Minority share	-0.0271 (-1.04)	-0.141* (-3.09)
Lender size	-0.0449* (-4.11)	-0.0513* (-4.59)
Constant	0.217* (2.92)	0.154** (2.05)
R^2	0.041	0.108
Observations	1 270 287	1 270 287

Notes: t statistics in parentheses; ***, ** and * indicate significance at the 1, 5 and 10 per cent level, respectively; standard errors are clustered at the lender and tract levels

7. Robustness Tests

The key hypothesis of the paper is that the OTD lenders became liquidity constrained when the securitisation market effectively shut down in 2007, and this increase in liquidity constraints, in turn, caused the OTD lenders to reduce new mortgage lending disproportionately. A key assumption underpinning this hypothesis, and the identification strategy, is that the OTD and non-OTD lenders are similar in all respects except the extent to which they became liquidity constrained during the crisis. There remains some possibility that the characteristics of OTD and non-OTD lenders differ along other unobservable dimensions, and that these differences could be driving the variation in lending behaviour across the two lender groups during the crisis. For example, OTD lenders may have been more willing to take risk or they may have been more reliant on specific loan origination channels that may have been associated with greater risk-taking (e.g. mortgage brokers). It could be these systematic differences, rather than differences in financing constraints, causing the observable variation in lending behaviour during the crisis. The purpose of the following series of tests is to rule out such alternative explanations for the observed link between securitisation and mortgage lending during the crisis.

7.1 Changes in Mortgage Lending Standards

Some empirical studies suggest that securitisation contributed to bad lending by reducing the incentives of lenders to carefully screen borrowers (Mian and Sufi 2009; Keys *et al* 2010; Rosen 2010; Purnanandam 2011). These studies argue that securitisation weakened lenders incentives to screen borrowers by making the link between loan originators and the investors who bear the default risk more opaque. It also led to asymmetric information between loan originators and final investors and, subsequently, moral hazard problems. This suggests that OTD lenders may have had weaker incentives to screen borrowers than non-OTD lenders. It could be that this pre-crisis difference in lending standards between the two groups, and not differences in financing constraints, caused difference in lending behaviour during the crisis.

I need to make some subtle changes to the estimating equation to test the robustness of my results to this alternative lending standards explanation. To start, I re-write the equation in levels:

$$L_{ijt} = \alpha + SALESHARE'_{ij}\beta + CRISIS'_t\gamma + SALESHARE_{ij} * CRISIS'_t\rho + X'_{ijt}\phi + \underbrace{\theta_i + \theta_j + \eta_{it} + \eta_{jt} + \varepsilon_{ijt}}_{v_{ijt}} \quad (4)$$

There are a couple of small, but important, differences between Equations (1) and (4). First, the subscript on the loan sale variable ($SALESHARE_{ij}$) indicates that the reliance on loan sales varies by lender *and* tract, rather than just lender. The highly disaggregated nature of the loan-level data means that the share of loans that are sold can be constructed for each lender in each tract. Second, the additional variation in the loan sales share variable due to this re-specification means that lender-specific time trends (η_{it}) can be separately identified within the error term. The lender-specific time trends control for unobservable bank-specific factors that vary systematically over time, such as changes in bank lending standards. The original specification could not include lender-specific dummies as these would be perfectly collinear with the sales share variable, which only varied by lender. This equation can again be written in growth rates by taking first differences over time:

$$\Delta L_{ij} = \gamma + SALESHARE'_{ij}\rho + \Delta X'_{ij}\phi + \underbrace{\Delta\eta_i + \Delta\eta_j + \Delta\varepsilon_{ij}}_{\Delta v_{ij}} \quad (5)$$

As discussed earlier, the OLS estimator of ρ is biased if unobservable credit demand shocks are correlated with a lender-tract's reliance on loan sales (i.e. $corr(SALESHARE_{ij}, \Delta\eta_j) \neq 0$). But, as before, this is easily handled by including tract dummies in Equation (5). However, the OLS estimator of ρ can now also be biased if unobservable credit supply shocks are correlated with a lender-tract's reliance on loan sales (i.e. $corr(SALESHARE_{ij}, \Delta\eta_i) \neq 0$). For example, if banks that were reliant on the originate-to-distribute model were also more likely to reassess their risk exposures and tighten lending standards during the crisis there could be a negative correlation between a lender-tract's reliance on loan sales and bank-specific lending growth (i.e. $corr(SALESHARE_{ij}, \Delta\eta_i) < 0$). By including a dummy variable for each lender in the growth rate equation, I control for unobservable changes in lending policies across financial institutions, including changes in lending standards. In other words, I can identify the

relationship between the pre-crisis reliance on securitisation and mortgage lending during the crisis after controlling for *both* unobservable tract-specific and lender-specific shocks. This eliminates any potential source of endogeneity caused by differences in the national lending policies of OTD and non-OTD lenders. The results of estimating Equation (5) are shown in Table 4.

	OLS	Tract fixed effects	Tract and lender fixed effects
Variable	(1)	(2)	(3)
Sale share	−0.111*** (−4.32)	−0.108*** (−4.20)	−0.102*** (−2.90)
Income growth	0.0678*** (7.43)	0.0631*** (6.97)	0.0700*** (26.54)
Minority share	−0.0288 (−1.50)	−0.0660** (−2.27)	−0.0213** (−2.23)
Lender size	−0.220*** (−12.51)	−0.222*** (−11.82)	−0.300*** (−19.75)
Constant	0.172*** (8.23)	0.178*** (8.41)	−0.00185 (0.00)
R^2	0.138	0.176	0.226
Observations	1 848 528	1 848 528	1 848 528

Notes: t statistics in parentheses; ***, ** and * indicate significance at the 1, 5 and 10 per cent level, respectively; standard errors are clustered at the lender and tract levels

The results of estimating the model using the lender-tract share of loan sales are very similar to the benchmark model that uses the lender share of loan sales. Based on the specification with just tract fixed-effects (column 2) the coefficient estimate is -0.108 , which is similar to the estimate of -0.077 obtained from the benchmark fixed-effects model (column 2 of Table 2). More importantly, the negative relationship between pre-crisis securitisation and lending activity during the crisis still holds even when I include both tract and lender fixed effects (column 3). In other words, the OTD lenders do not appear to have disproportionately reduced lending because of a relatively large (unobservable) tightening of bank lending standards. Rather, the link between loan sales and lending activity remains even after controlling for changes in bank lending policies. The estimates from the specification with both lender and tract fixed effects (column 3) suggests that a one standard deviation shock to the share of loans sold is associated with a 21 per cent decline in new mortgage credit.

7.2 Private versus Public Securitisation

A key assumption underpinning the benchmark model is that US mortgage lenders cannot easily substitute between different sources of funding, so the lenders that were dependent on securitisation would have become more liquidity constrained when the private-label market shut down in 2007.¹⁴ But this assumption may not hold if the mortgage lenders were able to substitute towards other less-affected sources of finance. For example, lenders that were particularly reliant on privately securitising mortgages may have sold their loans to the GSEs instead. The flow of funds data presented earlier suggested that, in aggregate, there was a substitution away from private securitised lending to public securitised lending during the crisis as the GSEs stepped into the breach caused by the disruption to the private-label market. In other words, the flow of funds evidence suggests that at least some lenders were able to substitute away from the worst-affected sources of finance.

The HMDA information can be used to identify each lender's reliance on both public and private loan sales. If the liquidity constraints hypothesis is true, the lenders most reliant on *private* securitisation in the pre-crisis period should have become more liquidity constrained than lenders dependent on public securitisation and hence would have scaled back credit by relatively more during the crisis.

To examine this, I re-estimate the benchmark equation but, for each bank, I split the share of loan sales into two components – the share of loans that are sold to the GSEs (*PUBSHARE*) and the share of loans that are sold to private financial institutions (*PRIVSHARE*):

$$\Delta L_{ij} = \gamma + PRIVSHARE'_i \beta_1 + PUBSHARE'_i \beta_2 + \Delta X'_{ij} \phi + \Delta \eta_j + \Delta \varepsilon_{ij} \quad (6)$$

If the liquidity constraints hypothesis is true, then there would be a significant negative effect of the private sale share variable (*PRIVSHARE*) on lending (i.e. $\beta_1 < 0$). Moreover, the effect of private securitisation would be greater than the

14 There is an additional assumption that borrowers are unable to perfectly offset funding shocks by substituting towards other sources of external finance. This assumption is more likely to hold in housing finance than in corporate finance because corporations typically have greater access than households to other funding sources (e.g. public debt and equity markets). Moreover, it is generally costly to re-apply for credit if the borrower's initial application is rejected. In other words, if there is a supply-side effect of the liquidity shocks, it is likely to be particularly important for household lending.

effect of public securitisation ($\beta_1 < \beta_2$). If, instead, public securitisation had a larger (negative) effect on lending, then this may be evidence of a confounding factor, related to the OTD business model, causing all such lenders to cut credit. The results are shown in Table 5.

Table 5: Private and Public Securitisation

Variable	OLS (1)	Tract fixed effects (2)
Private sale share	-0.102*** (-2.85)	-0.0816** (-2.19)
Public sale share	-0.0527 (-0.67)	-0.0583 (-0.72)
Income growth	0.0719*** (8.92)	0.0679*** (8.71)
Minority share	-0.0360** (-2.15)	-0.0824*** (-3.83)
Lender size	-0.0226*** (-3.29)	-0.0226*** (-3.16)
Constant	0.0960 (1.53)	0.0945 (1.40)
R^2	0.016	0.062
Observations	1 848 528	1 848 528

Notes: t statistics in parentheses; ***, ** and * indicate significance at the 1, 5 and 10 per cent level, respectively; standard errors are clustered at the lender and tract levels

A comparison of the coefficient estimates on the private and public sale share variables (rows 1 and 2) suggests that the effect of the liquidity shock on lending activity is significantly larger for the private sale share than for the public sale share. This is confirmed in a separate t -test that directly compares the two coefficient estimates. The estimated effect of the private sale share on lending activity is also economically larger than the effect for the total sale share shown in Table 2. A one standard deviation shock to the private sale share variable is associated with a 16 per cent decline in new mortgage credit. This supports the hypothesis that OTD lenders reduced lending because they became financially constrained in 2007 and not because of some other unobservable confounding factor affecting all lenders that are reliant on the originate-to-distribute model.

7.3 Affiliated Non-bank Mortgage Lenders

To test the relative merits of the liquidity constraints hypothesis, I construct another test in which I focus specifically on OTD lenders. Many OTD lenders are mortgage companies that specialise in home mortgage lending, whereas most non-OTD lenders are depository institutions. These mortgage companies typically rely solely on securitisation to finance their lending, and generally cannot fund themselves through alternative sources of finance, such as deposits. However, there are important differences *within* the pool of OTD lenders. For instance, some mortgage companies are affiliated with depository institutions, such as Citigroup, whereas others are not. The mortgage companies that are affiliated with a bank potentially have access to a more diversified funding base (through internal capital markets) than mortgage companies that are not affiliated. We might therefore expect the affiliated mortgage companies to be relatively less vulnerable to a funding shock that is specific to the securitisation market than the non-affiliated companies.

This variation across OTD lenders in the ability to diversify funding risk allows me to test the liquidity constraints hypothesis against alternative explanations for the link between pre-crisis reliance on securitisation and post-crisis mortgage lending. If the liquidity constraints hypothesis is true, the lending of non-affiliated mortgage companies (that are solely reliant on securitisation) should be more responsive to the liquidity shock than the lending of affiliated mortgage companies. So I re-estimate the benchmark equation to test the liquidity constraints hypothesis, but now focus on the subset of mortgage companies (that are predominantly OTD lenders):

$$\Delta L_{ij} = \gamma + NONAFFILIATED_i * SALESHARE_i' \beta_1 + SALESHARE_i' \beta_2 + \Delta X_{ij}' \phi + \Delta \eta_j + \Delta \varepsilon_{ij} \quad (7)$$

where I include a dummy variable for whether the lender is affiliated with a commercial bank or not. The dummy variable *NONAFFILIATED* takes a value of one if the lender is not affiliated with a bank and is zero otherwise. The dummy variable is interacted with the share of loans sold by each lender. All the other variables are as before. Under the liquidity constraints hypothesis, the negative effect of the liquidity shock should be larger for the non-affiliated lenders (i.e. $\beta_1 < 0$). The results are shown in Table 6.

Table 6: New Mortgage Lending by Non-bank Lenders

Variable	OLS (1)	Tract fixed effects (2)
Non-affiliated x sale share	−0.0457 (−0.66)	−0.0419 (−0.59)
Sale share	−0.0822 (−1.39)	−0.0607 (−1.00)
Income growth	0.0607*** (4.14)	0.0585*** (4.14)
Minority share	−0.0626*** (−2.64)	−0.0935** (−2.56)
Lender size	−0.0349*** (−3.34)	−0.0396*** (−3.47)
Constant	0.226** (12.10)	0.261** (2.24)
R^2	0.020	0.097
Observations	926 679	926 679
Notes: t statistics in parentheses; ***, ** and * indicate significance at the 1, 5 and 10 per cent level, respectively; standard errors are clustered at the lender and tract levels		

In both columns 1 and 2, the coefficient estimate on the interaction term *NONAFF * SALESHARE* is negatively signed. This suggests that the non-affiliated mortgage companies, which lacked alternative funding sources, had a greater tendency than the affiliated mortgage companies to reduce lending in response to the liquidity shock. However, the coefficient estimate on the interaction term is not statistically significant. So, overall, the results only provide tentative evidence to support the liquidity constraints hypothesis.

7.4 The Aggregate Effect of the Liquidity Shock

The ‘within-tract’ identification strategy does not provide the complete picture of the aggregate effect of the liquidity shock on mortgage lending. This is because the strategy implicitly does not allow borrowers to substitute between different lenders (where Census tracts are thought of as ‘borrowers’). But borrowers might compensate for any reduction in credit from OTD lenders by obtaining alternative finance from non-OTD lenders. This substitution towards unaffected lenders could limit the effect of the liquidity shock on aggregate mortgage lending.

One approach to identify the aggregate effect of the liquidity shock on mortgage lending would be to estimate the relationship between the tract-level lending growth and the tract-level share of loans sold, which would implicitly allow borrowers to substitute between lenders. As discussed earlier, the estimates from such a regression will be biased if changes in total mortgage credit at the tract level reflect both changes in credit demand and supply.

Jimenez *et al* (2011) have recently proposed a method to adjust these estimates for the bias using the (unbiased) coefficient estimates obtained at the lender-tract level. This approach effectively separates the impact of supply from demand while allowing borrowers to substitute between lenders. The approach is described in more detail in Appendix C. To do this, I estimate the tract-level version of Equation (2):

$$\bar{\Delta}L_j = \gamma + SALE\bar{SHARE}'_j \rho + \bar{X}'_j \phi + \Delta\eta_j + \Delta\bar{\epsilon}_j \quad (8)$$

where $\bar{\Delta}L_j$ denotes the log change in credit for tract j across all mortgage lenders. It is essentially a weighted average of the growth rate of credit at the lender-tract level, where the weights are given by each lender's share of loans within each tract. Similarly, $SALE\bar{SHARE}_j$ denotes the (weighted) average pre-crisis reliance on loan sales of lenders that grant credit to tract j . The specification includes a set of tract-level control variables, such as the average income growth of loan applicants (\bar{X}_j). The same credit demand shock ($\Delta\eta_j$) appears in Equations (2) and (8) assuming that the shock affects a tract's borrowing from each lender equally. I then adjust these estimates using the following formula (which is outlined in Appendix C):

$$\bar{\rho} = \hat{\rho}_{OLS} - (\hat{\rho}_{OLS} - \hat{\rho}_{FE}) * \frac{V(SALESHARE_i)}{V(SALE\bar{SHARE}_j)}$$

The results of estimating Equation (8) are shown in Table 7. As the first row of the table indicates, the OLS estimate of the aggregate effect ($\hat{\rho}_{OLS}$) is -0.364 . Recall that the lender-tract level OLS estimate ($\hat{\rho}_{OLS}$) is -0.094 and the fixed-effects estimate ($\hat{\rho}_{FE}$) is -0.077 . Moreover, the data suggest that the sample variance of the share of loans sold at the lender level ($V(SALESHARE_i)$) is about 0.012 while the sample variance of the share of loans sold at the tract level ($V(SALE\bar{SHARE}_j)$) is about 0.116. Combining all these estimates, and using the adjustment formula,

the unbiased estimate of the aggregate effect of the liquidity shock ($\hat{\rho}$) is -0.207 (that is, $-0.207 = -0.364 - (-0.094 + 0.077) * (0.012/0.116)$).

Table 7: Aggregate New Mortgage Lending

Variable	OLS (1)
Sale share	-0.364*** (-48.70)
Income growth	0.139*** (24.75)
Minority share	-0.0803*** (-23.62)
Lender size	-0.0304*** (-28.90)
Constant	0.401*** (45.89)
R^2	0.194
Observations	63 269

Notes: t statistics in parentheses; ***, ** and * indicate significance at the 1, 5 and 10 per cent level, respectively; standard errors are clustered at the tract level

Overall, the results imply that a one standard deviation increase in the share of loans sold in aggregate is associated with a decline in new mortgage lending of around 2.3 per cent, on average. In aggregate, new mortgage lending fell by around 16.7 per cent, so a one standard deviation increase in the share of loans sold can explain about 14 per cent of the aggregate fall in new mortgage credit. This estimated (general equilibrium) effect is very similar to the (partial equilibrium) effect identified at the more disaggregated lender-tract level. This suggests that there was very little substitution between OTD and non-OTD lenders by borrowers following the liquidity shock.

8. Conclusion

The sharp contraction in new residential mortgage lending in the United States over 2007–2008 is often attributed to a significant tightening in credit conditions. However, there has been little formal testing of the extent to which this can be attributed to a reduction in credit supply. I fill this gap by examining the extent to which the fall in US residential mortgage credit over 2007–2008 was caused by a reduction in credit supply which, in turn, can be traced to a fall in liquidity.

Controlling for unobservable credit demand shocks that may be correlated with borrower risk, I show that mortgage lenders that were particularly reliant on loan securitisation reduced credit disproportionately during the crisis. This result is robust to a series of tests that are designed to rule out alternative explanations for the link between pre-crisis reliance on securitisation and mortgage lending during the crisis. For example, the results are upheld when I control for unobservable changes in bank risk-taking through lender-specific time trends. In other words, systematic differences in lending standards between OTD and non-OTD lenders do not appear to explain the variation in lending behaviour. Moreover, focusing just on lenders reliant on the OTD business model, I find that mortgage companies that were not affiliated with a commercial bank cut credit by more than affiliated companies. Assuming that the affiliated mortgage companies had better access to alternative sources of funding, this provides further support for the liquidity constraints explanation.

I also find that the effect of the liquidity shock on lending activity was particularly strong for lenders that were reliant on selling loans to private, rather than public, financial institutions. This is again consistent with the liquidity constraints hypothesis as it was the private-label securitisation market that was most adversely affected when capital market investors withdrew funding in late 2007. In contrast, the public securitisation market largely remained liquid due to active government support. Furthermore, I find little evidence that borrowers substituted away from the affected OTD lenders, which implies that the adverse liquidity shock had a significant impact on the aggregate level of new mortgage credit as well.

However, I do not find that the most affected lenders disproportionately reduced credit to risky borrowers, suggesting that any flight to quality was not driven by the liquidity shock but by other changes in lending behaviour. Furthermore, I do not find evidence to indicate that the affected lenders disproportionately reduced credit to non-local borrowers, which suggests that the liquidity shock did not necessarily cause a flight to home.

Appendix A: Identifying the Effect of Credit Supply Shocks

In this Appendix I outline a model that describes how credit demand and supply shocks affect mortgage lending. The model is closely related to that of Khwaja and Mian (2008). The purpose of the model is to highlight the identification problem and explain the construction of the estimator that controls for credit demand shocks. In this simple model I assume that each bank i lends to region j at time t the amount L_{ijt} . There are two time periods. I assume that each bank can lend to only one region, but a region can borrow from multiple banks. On the credit supply side, I assume that each bank loan to a particular region is financed through a combination of securitisation S_{it} and other forms of external financing W_{it} . These assumptions generate the following flow of funds constraint:

$$L_{ijt} = S_{it} + W_{it}$$

I assume that the bank can securitise loans at no cost, but, importantly, there is a quantitative limit on how much the bank can securitise (i.e. $S_{it} < \bar{S}$). Beyond this limit, the bank must turn to costly external finance to support higher levels of lending. These assumptions ensure that the level of securitisation matters to the lending decision of each bank. If there was no limit on securitisation and/or no cost of accessing external finance, then the funding structure of the bank would not affect lending.¹⁵ Under this set of assumptions, the marginal cost of lending for the bank is solely a function of the volume of wholesale debt (i.e. external finance):

$$MC_{ijt} = \gamma W_{it}$$

The cost parameter ($\gamma > 0$) denotes the slope of the marginal cost curve. On the credit demand side, I assume the marginal loan return is given by the following equation:

$$MR_{ijt} = \bar{r}_{jt} - \alpha L_{ijt}$$

The borrower quality parameter (\bar{r}_{jt}) allows for variation in loan returns across regions. Given the slope parameter (α) is a positive constant, the formulation

¹⁵ I further assume that the bank cannot fund loans through internal finance (e.g. retained earnings or deposits). While this appears to be a strong assumption, it is only made to simplify the algebra – the results still hold if I instead assume that banks finance lending through deposits (D_{it}), where deposits are the cheapest form of funding. In that case, the key assumptions are that there is also a quantitative limit on internal finance (i.e. $D_{it} < \bar{D}$) and that securitisation is a cheaper form of funding than other forms of external finance.

assumes that there are diminishing marginal returns to borrowing. I solve for the first-period equilibrium by equating marginal revenue with marginal cost and substituting the flow of funds identity:

$$L_{ijt}^* = \frac{1}{\alpha + \gamma} (\bar{r}_{jt} + \gamma S_{it})$$

where the superscript ‘*’ denotes equilibrium. At the end of the first period, the credit market experiences two types of shocks:

1. Credit demand shock: $\bar{r}_{jt+1} = \bar{r}_{jt} + \bar{\eta} + \eta_j$
2. Credit supply shock: $S_{it+1} = S_{it} + \bar{\delta} + \delta_i$.

The credit demand shock consists of two terms – an aggregate shock that is common to all regions ($\bar{\eta}$) and an idiosyncratic shock that is specific to each region (η_j). In terms of the econometric framework, the aggregate credit demand shock might be an unexpected change in US monetary policy while the region-specific demand shock might be a shock to regional house prices. The credit supply shock also consists of two terms – an aggregate shock that is common to all banks ($\bar{\delta}$) and a bank-specific shock (δ_i). The aggregate credit supply shock might reflect some change in financial regulation that affects the ability of banks to securitise loans while the bank-specific credit supply shock could reflect each bank’s ability to securitise assets.

Following the same approach as before, I solve for the second-period equilibrium:

$$L_{ijt+1}^* = \frac{1}{\alpha + \gamma} (\bar{r}_{jt+1} + \gamma S_{it+1})$$

As the two solutions are linear, I can then take the difference in (equilibrium) lending over time ($\Delta L_{ij}^* = L_{ijt+1}^* - L_{ijt}^*$) to obtain:

$$\Delta L_{ij}^* = \frac{(\bar{\eta} + \eta_j)}{(\alpha + \gamma)} + \frac{\gamma(\bar{\delta} + \delta_i)}{(\alpha + \gamma)}$$

The change in the amount of each loan consists of two terms. The first term on the right-hand side denotes the impact of the region-specific credit demand shocks. The second term denotes the impact of the bank-specific supply shocks. If there is no cost of external finance ($\gamma = 0$), the credit supply shocks will not affect

the equilibrium growth rate of lending; lending growth will only be a function of demand shocks. In other words, credit supply shocks only matter if there are financing frictions on the lender side.

Now suppose I re-arrange the equation to combine all the aggregate shocks in a single term and have two separate terms for the bank-specific and region-specific shocks:

$$\Delta L_{ij}^* = \frac{(\bar{\eta} + \gamma\bar{\delta})}{(\alpha + \gamma)} + \frac{\gamma\delta_i}{(\alpha + \gamma)} + \frac{\eta_j}{(\alpha + \gamma)}$$

If I assume that the share of loans that are securitised ($SALESHARE_i$) by each bank is a suitable proxy for the bank-specific credit supply shock (δ_i) then I could run the OLS regression:

$$\Delta L_{ij}^* = \beta_0 + SALESHARE_i' \beta_1 + \underbrace{\eta_j + \varepsilon_{ij}}_{v_{ij}}$$

where there is an intercept that captures all the aggregate effects ($\beta_0 = \frac{(\bar{\eta} + \gamma\bar{\delta})}{(\alpha + \gamma)}$), a slope coefficient ($\beta_1 = \frac{\gamma}{(\alpha + \gamma)}$) that captures the relationship of interest and a composite error term (v_{ij}) which consists of a region-specific component (η_j) and a bank-region specific component (ε_{ij}). If the share of loans that are securitised ($SALESHARE_i$) is correlated with the unobservable credit demand shocks (η_j) then the OLS estimate of β_1 will be biased. But suppose the region borrows from both an OTD lender and a non-OTD lender. Denote the OTD lender with subscript O and the non-OTD lender with subscript N . For a region j that has a loan from each type of bank, the within-region difference in lending growth is:

$$\Delta L_{Oj} - \Delta L_{Nj} = (SALESHARE_O - SALESHARE_N)' \beta_1 + (\eta_j - \eta_j) + (\varepsilon_{Oj} - \varepsilon_{Nj})$$

This equation eliminates both the effect of the aggregate shocks and the unobservable region-specific credit demand shocks. Equivalently, the OLS regression with the inclusion of borrower-specific fixed effects controls for the unobservable credit demand shocks (η_j). An unbiased estimate of the causal effect of the credit supply shock can be obtained under the identifying assumption that each bank's loan securitisation share is uncorrelated with the bank-region specific errors ($corr(SALESHARE_i, \varepsilon_{ij}) = 0$).

Appendix B: Identifying the Separate Effects of Liquidity and Lending Standards Shocks

I now modify the model to allow for changes in bank lending standards. I maintain all the assumptions on the demand side of the credit market, but make two slight changes to the supply side. First, identification now requires an assumption that each bank loan to a particular region is ‘locally financed’. For example, if there is a negative funding shock to the Californian subsidiary of Bank of America then that subsidiary cannot obtain replacement finance through an internal transfer from the New York subsidiary. In other words, I assume that it is prohibitively costly for different lending units within a financial institution to cross-subsidise each other’s lending. This assumption implies that the flow of funds constraint becomes:

$$L_{ijt} = S_{ijt} + W_{ijt}$$

Second, I assume that the bank must exert some costly ‘screening effort’ (E_{it}) to originate each loan. The effort exerted in screening borrowers can be loosely thought of as the bank’s lending standards; a bank that exerts more effort has stricter lending standards. I assume that the cost of screening is given by a convex function ($\frac{\phi E_{it}^2}{2}$). Under this set of assumptions, the marginal cost of lending for the bank is a function of the volume of external finance *and* the level of screening effort:

$$MC_{ijt} = \gamma W_{ijt} + \phi E_{it}$$

As before, the marginal loan return is given by:

$$MR_{ijt} = \bar{r}_{jt} - \alpha L_{ijt}$$

Solving for the first-period equilibrium by equating marginal revenue with marginal cost:

$$L_{ijt}^* = \frac{1}{\alpha + \gamma} (\bar{r}_{jt} + \gamma S_{ijt} - \phi E_{it})$$

At the end of the first period, the credit market now experiences three shocks. There is the same demand shock as before, but now there are two types of credit supply shocks; there is a liquidity shock and a new shock to screening effort (or ‘lending standards shock’):

1. Credit demand shock: $\bar{r}_{jt+1} = \bar{r}_{jt} + \bar{\eta} + \eta_j$
2. Credit supply (liquidity) shock: $S_{ijt+1} = S_{ijt} + \bar{\delta} + \delta_{ij}$
3. Credit supply (lending standards) shock: $E_{it+1} = E_{it} + \bar{\psi} + \psi_i$.

The liquidity shock is similar to before, except that it is now specific to each bank and region (δ_{ij}) rather than specific to each bank. The new lending standards shock comprises two components: an aggregate shock ($\bar{\psi}$), such as a change in loan screening technology (e.g. the availability of credit scoring), and a bank-specific shock (ψ_i), such as a change in bank risk preferences.

Following the same approach as before, I solve for the second-period equilibrium:

$$L_{ijt+1}^* = \frac{1}{\alpha + \gamma} (\bar{r}_{jt+1} + \gamma S_{ijt+1} - \phi E_{it+1})$$

Taking the difference in (equilibrium) lending over time I obtain:

$$\Delta L_{ij}^* = \frac{(\bar{\eta} + \eta_j)}{(\alpha + \gamma)} + \frac{\gamma(\bar{\delta} + \delta_{ij})}{(\alpha + \gamma)} - \frac{\phi(\bar{\psi} + \psi_i)}{(\alpha + \gamma)}$$

Compared to the basic model, this equation now has an additional term on the right-hand side, which denotes the impact of the lending standards shock. Note that if there is no cost of screening loans ($\phi = 0$), then the lending standards shock has no effect on the equilibrium growth rate of lending.

Re-arranging the equation to combine all the aggregate shocks in a single term leads to three separate terms for the bank-region-specific, region-specific and bank-specific shocks:

$$\Delta L_{ij}^* = \frac{(\bar{\eta} + \gamma\bar{\delta} - \phi\bar{\psi})}{(\alpha + \gamma)} + \frac{\gamma\delta_{ij}}{(\alpha + \gamma)} + \frac{\eta_j}{(\alpha + \gamma)} - \frac{\phi\psi_i}{(\alpha + \gamma)}$$

If the share of loans that are sold ($SALESHARE_{ij}$) by each bank in each region is assumed to be a suitable proxy for the liquidity shock (δ_{ij}) then the following equation can be estimated:

$$\Delta L_{ij}^* = \beta_0 + SALESHARE'_{ij}\beta_1 + \underbrace{\eta_j + \psi_i + \varepsilon_{ij}}_{v_{ij}}$$

where there is an intercept that captures all the aggregate effects ($\beta_0 = \frac{(\bar{\eta} + \gamma\bar{\delta} - \phi\bar{\psi})}{(\alpha + \gamma)}$), a slope coefficient ($\beta_1 = \frac{\gamma}{(\alpha + \gamma)}$) that captures the relationship of interest, and a composite error term (v_{ij}) that includes an unobservable region-specific component (η_j), an unobservable bank-specific component (ψ_i) and a bank-region specific component (ε_{ij}).

This equation can be estimated by OLS including borrower-specific fixed effects to control for the unobservable credit demand shocks (η_j) and bank-specific fixed effects to control for the unobservable lending standards shocks (ψ_i). An unbiased estimate of the causal effect of the liquidity shock can be obtained by assuming that the share of loans sold by each bank in each region is uncorrelated with the bank-region specific errors (i.e. $\text{corr}(\text{SALESHARE}_{ij}, \varepsilon_{ij}) = 0$).

Appendix C: Estimating the Unbiased Aggregate Effect of the Liquidity Shock

Jimenez *et al* (2011) outline a methodology to estimate the unbiased aggregate effect of the liquidity shock on new lending growth. The model is estimated at the level of the Census tract and the implied coefficient estimates are adjusted for bias using coefficient estimates obtained at the more disaggregated lender-tract level. The approach separates the impact of supply from demand, while taking into account general equilibrium adjustments by borrowers.

It is helpful to outline the methodology in a few steps. For simplicity, suppose there are no control variables. Recall Equation (2) (without controls) estimated at the lender-tract level:

$$\Delta L_{ij} = SALESHARE_i' \beta + \eta_j + \varepsilon_{ij} \quad (C1)$$

But I want to estimate the tract-level version of this equation:

$$\bar{\Delta} L_j = SALE\bar{SHARE}_j' \beta + \eta_j + \bar{\varepsilon}_{ij} \quad (C2)$$

where $\bar{\Delta} L_j$ denotes the log change in credit for tract j across all mortgage lenders. It is a weighted average of the growth rate of credit at the lender-tract level, where the weights are given by each lender's share of loans within each tract. It is not a simple unweighted average of ΔL_j because tracts can start borrowing from new mortgage lenders. The tract-level measure of new lending is constructed by adding up the total number of new loans originated by each mortgage lender within a given tract each year. Similarly, $SALE\bar{SHARE}_j$ denotes the (weighted) average pre-crisis reliance on loan sales of lenders that grant credit to tract j . This variable is slightly more complicated to construct as it requires converting a measure of the share of loans that are sold by each lender ($SALESHARE_i$) into a measure of the share of loans that are sold within each tract ($SALE\bar{SHARE}_j$). The tract-specific measure of loans sold is constructed using the following formula:

$$SALE\bar{SHARE}_j = \sum_{i=1}^{N_j} w_{ij} * SALESHARE_i$$

where $w_{ij} = L_{ij}/L_j$ is the share of new loans originated by lender i within each tract j and N_j is the set of lenders that originate loans in tract j . Note also that the same credit demand shock (η_j) appears in both Equations (C1) and (C2) under the assumption that the shock affects a tract's borrowing from each lender equally.

Recall that the OLS estimate of the (partial equilibrium) effect of the liquidity shock at the lender-tract level is given by:

$$\hat{\beta}_{OLS} = \beta + \frac{cov(SALESHARE_i, \eta_j)}{V(SALESHARE_i)} \quad (C3)$$

Also, recall that the fixed-effects (FE) estimate (that controls for credit demand shocks) provides an unbiased estimate of the effect of the liquidity shock:

$$\hat{\beta}_{FE} = \beta \quad (C4)$$

Combining these two conditions we obtain:

$$\hat{\beta}_{OLS} - \hat{\beta}_{FE} = \frac{cov(SALESHARE_i, \eta_j)}{V(SALESHARE_i)} \quad (C5)$$

Now the OLS estimate of the aggregate (general equilibrium) effect of the liquidity shock at the tract level is given by:

$$\hat{\beta}_{OLS} = \bar{\beta} + \frac{cov(SALE\bar{SHARE}_j, \eta_j)}{V(SALE\bar{SHARE}_j)} \quad (C6)$$

But this will be biased if there is any correlation between the share of loans sold in a particular tract and unobservable tract-specific trends, such as shocks to local housing prices. We cannot follow the same procedure as before and estimate a fixed-effects version of Equation (C2) because the unobservable tract-specific fixed effect (η_j) is collinear with the key explanatory variable ($SALE\bar{SHARE}_j$). However, if the correlation between the share of loans sold and the demand shocks is the same across all banks, then the following condition holds:

$$\begin{aligned} cov(SALE\bar{SHARE}_j, \eta_j) &= cov(\sum_{i=1}^{N_j} w_{ij} * SALESHARE_i, \eta_j) \\ &= cov(SALESHARE_i, \eta_j) \end{aligned} \quad (C7)$$

Combining Equations (C5), (C6), (C7) we obtain the aggregate bias-adjustment formula:

$$\bar{\beta} = \hat{\beta}_{OLS} - (\hat{\beta}_{OLS} - \hat{\beta}_{FE}) * \frac{V(SALESHARE_i)}{V(SALE\bar{SHARE}_j)} \quad (C8)$$

This is the formula used to obtain the unbiased estimate of the aggregate effect of the liquidity shock presented in the paper. Importantly, both the variance of the bank-specific liquidity shocks ($V(SALESHARE_i)$) and the variance of the (weighted) tract-specific liquidity shocks ($V(SALE\bar{SHARE}_j)$) can be obtained from the data. This means that all the terms on the right-hand side of the equation can be estimated, providing an unbiased estimate of the aggregate effect of the liquidity shock ($\bar{\beta}$).

Appendix D: The Measurement of Subprime Mortgage Lending

There are two problems with using the share of high-priced loans as an indicator of risky (or subprime) lending. First, it may be biased as the share of high-priced mortgages can change over time due to changes in the yield curve rather than changes in bank lending policies (Mayer and Pence 2008). The HMDA does not collect information directly on the interest rate spread, but rather estimates the spread from information it collects on the interest rate of each loan. For example, to calculate the interest rate spread on an adjustable-rate mortgage (ARM) with a contract maturity of 30 years, the HMDA uses the interest rate on a 30-year Treasury bond even though the interest rate on the loan may actually be priced off a shorter-term security. In other words, the maturity of the loan is assumed to correspond to the maturity of the loan contract, not the expected maturity of the loan (which is more likely to be used by the lender). As short-term rates are generally lower than long-term rates, subprime ARMs are likely to be under-reported in the data (because there will be fewer loans reported with a sufficiently large interest rate spread).

Second, the extent of this bias shifts over time as the slope of the yield curve changes. For instance, if longer-term rates fall relative to short-term rates (i.e. the yield curve becomes flatter), the measured share of subprime ARMs will rise as a result of this bias. It is estimated that at least 13 per cent of the increase in the number of higher-priced loans in the HMDA data between 2004 and 2005 was attributable to a flattening of the yield curve (Avery, Brevoort and Canner 2007).

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