Liar's Loans, Mortgage Fraud, and the Great Recession

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Abstract

Losses in the market for private label residential mortgage backed securities (RMBS) were at the epicenter of the financial crisis from 2007-2008. Existing research has shown that a substantial portion of the poor performance of the loans securitized in this market was caused by fraudulent practices or misrepresentation. However, to date no paper has estimated the effects of mortgage fraud on losses in foreclosure in this market. This paper fills this gap by 1) Accounting for total losses to foreclosure due to no/low documentation loans which were known colloquially within the industry as "Liar's Loans," and 2) Estimating what portion of these losses can be considered excess from the perspective of the investor. Losses are considered "excess" in the sense that losses were greater than if the information about loan quality disclosed to investors in offering documents had been accurate, instead of fraudulent. I find that Liar's Loans account for roughly 70% of total losses. The estimated conservative lower bound for what portion of losses in Liar's Loans can be considered excess is 30%. Projected to the level of the entire market, this implies that $345 billion of the $500 billion in losses to foreclosure in this market are accounted for by Liar's Loans. Roughly $100 billion, or 20% of total market losses, can be considered excess losses caused by fraud in Liar's Loans.

1 Introduction

Losses in private label residential mortgage backed securities (RMBS) were at the epicenter of the financial crisis. These losses caused the failure of institutions heavily invested in them, as well as the failure of institutions like Bear Stearns or AIG that were invested in complex derivatives based on them such as collateralized debt obligations or credit default swaps. Existing economic research has shown that a substantial portion of the defaults in the loans used

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to collateralize these securities was associated with fraudulent or negligent origination practices,[1] that fraud was particularly severe in no/low documentation loans known colloquially within the industry as "Liar's Loans", and that the quality of these loans was systematically misrepresented to the investors that purchased these securities by all major intermediaries involved in the sales of mortgages (Ben-David, 2011; Black, 2013; Garmaise, 2015; Griffin and Maturana, 2014*b*; Jiang, Nelson and Vytlacil, 2014; Keys et al., 2010; Mian and Sufi, 2015; Piskorski, Seru and Witkin, 2013). However, as of writing the no paper has yet estimated the effect of fraud on losses to foreclosure in the loans used as collateral for these securities.

This paper seeks to fill this gap by 1) Accounting for total losses to foreclosure due Liar's Loans, and 2) Estimating what portion of total losses can be considered excess from the perspective of the investor. Losses for Liar's Loans are considered "excess" if they are greater than those that would have occurred if the loan quality information disclosed to investors had been accurate instead of fraudulent. The main findings in this paper suggest that losses in foreclosure due to fraud in this market were substantial, prolonged throughout the entire crisis and Great Recession from 2007-2012, and concentrated in economically fragile geographic areas. Losses in Liar's Loans account for roughly 70% of total losses in the data and 30% Liar's Loans losses of can be considered excess. Projected to the level of the entire market, this implies that no/low documentation loans can account for approximately $345 billion of the $500 billion in losses in this market, $100 billion of which can be considered excess. Moreover, 44% of total losses occurred in ZIP codes with the highest levels of fraudulent income overstatement on mortgage applications. These areas were particularly poorly suited to bear these losses, and the prolonged losses to foreclosure in these neighborhoods helps to explain the terrible economic performance of these areas throughout the Great Recession.

The research design pursued in this paper identifies the causal effects of fraud on losses to foreclosure by comparing losses on loans in the no/low documentation treatment group, with losses on loans with similar observable risk measures in the full documentation control group. Systematically larger losses in the treatment group are consistent with the causal effects of fraud. The main problem with this research design discussed in the empirical literature is the presence of fraud in the full documentation control group, which would cause this comparison to understate true excess losses caused by fraud (Jiang, Nelson and Vytlacil, 2014; Griffin and Maturana, 2014*b*). To address this issue, qualitative information on high fraud originators from lawsuits regarding the actual loans in the dataset[2] is used to refine the control group by removing loans originated by these institutions. Additionally, loans from ZIP codes with high levels of fraudulent income overstatement on mortgage applications are removed from the control group. Regression discontinuity models based on those in the literature are then used to confirm the presence of fraud in the full documentation

[1] The term fraud is used in this article in the economic sense and should not be seen as having any legal significance. See page 5 for a full definition.

[2] These lawsuits are discussed in section 3.3.

control group, as well as show that the refined full documentation control group is meaningfully freer of fraud.

In addition to the contribution to the empirical research on fraud, the findings in this paper are broadly relevant for research on macroprudential financial regulation, and research on the role of household balance sheets in the financial crisis. The estimate of excess losses to foreclosure is significant for financial regulation because these losses have caused numerous lawsuits from investors who claim they were defrauded by the major financial institutions that misrepresented the quality of the mortgages in the offering documents for the securities they purchased. Market regulations and contractual obligations that require the accurate disclosure of asset quality are a necessary condition for the basic functioning of capital markets. However, this minimum condition was not met on a widespread basis because all reputable intermediaries involved in the sale of mortgages were engaged in systematic misrepresentation (Griffin and Maturana, 2014*b*; Piskorski, Seru and Witkin, 2013). The basic issue underlying these lawsuits is succintly summarized in a recent ruling by District Judge Denise Cote,

> "This case is complex from almost any angle, but at its core there is a single, simple question. Did the defendants accurately describe the home mortgages in the Offering Documents for the securities they sold that were backed by those mortgages? Following trial, the answer to that question is clear. The offering documents did not correctly describe the mortgage loans. *The magnitude of falsity, conservatively measured, is enormous.*
>
> Given the magnitude of falsity, it is perhaps not surprising that in defending this lawsuit defendants did not opt to prove that the statements in the Offering Documents were truthful."[3] [emphasis added]

From the perspective of the investor, the estimate of excess losses is significant because it measures how much more Liar's Loans lost in foreclosure than if the offering documents had accurately described the quality of the mortgages, rather than misrepresented it. To eliminate the problems in this market, financial regulation will likely need to prioritize increased monitoring of financial institutions, enforcement of penalties for violations of disclosure rules including criminal prosecution for financial institution executives involved in misrepresentation, increase investor recourse for violations of stated representations, and limit extreme compensation packages for executives to reduce incentives for looting.

[3] From ruling in *Federal Housing Finance Agency v. Nomura Holding America*, May 11th, 2015. The FHFA sued 16 trustees for misrepresentations made in offering documents and prospectuses for securities sold to Fannie Mae and Freddie Mac. All but Nomura and Royal Bank Scotland settled out of court, and the court ruled against these institutions in trial on May 11th, 2015. Accessed on June 26th, 2015 from: `https://s3.amazonaws.com/s3.documentcloud.org/documents/2077713/ruling-on-mortgage-fraud-in-2008-crisis.pdf`

The findings are also relevant for historical narratives of the role of household balance sheets in the financial crisis because losses to foreclosure imply that household wealth had already been entirely wiped out. In addition to loss of wealth for the individual homeowner, losses to foreclosure have substantial negative externalities that cause needless loss of wealth for everyone in a neighborhood. Research has shown that the fire sale of homes caused by large numbers of foreclosures during the financial crisis reduced house prices lower than they otherwise would have fallen, and can account for roughly one-third of the fall in house prices. The reduction in house prices further impaired household balance sheets, thereby reducing aggregate demand. Estimates suggest the causal effects of foreclosures during the crisis were responsible for roughly one-fifth of the decline in residential investment and auto-sales (Mian, Sufi and Trebbi, 2014). Moreover, many of the investors in these securities were institutional investors such as retirement and pension funds. Therefore losses in these securities also contributed to losses of household wealth and retirement savings.

The prolonged losses to foreclosure due to fraud that were concentrated in economically fragile areas also help to explain the lack of recovery in these places. The financial panic had largely subsided by 2009. However losses to foreclosure in private label RMBS were much more prolonged, and remained at a high level of close to $100 billion per year from 2010-2012. Fully 44% of the losses to foreclosure from 2008-2012, or roughly $220 billion, occurred in ZIP codes with the highest levels of fraudulent income overstatement on mortgage applications. These ZIP codes were particularly poorly suited to bear these losses because in the pre-crisis period they had low average credit scores, low income, high poverty rates, and high unemployment. Research has shown that these ZIP codes experienced terrible economic performance throughout the course of the crisis, including negative income growth, increased poverty, and increased unemployment (Mian and Sufi, 2015).

2 Literature Review

The literature review in this section provides the necessary background context for understanding how the main results contribute to the existing research on mortgage fraud. The existing empirical research has directly observed numerous forms of fraud, and estimated the effects of fraud on increasing the probability of default. The basic description of fraud that emerges from this body of research is that executives of institutions that originated loans to be securitized in the private label market had perverse incentives based on the volume of loans originated, rather than the quality. To increase origination volume, these institutions systematically abandoned underwriting standards or falsified documents outright. These practices were particularly severe in no/low documentation loans that did not require documentation of income, assets, or employment, and were thus named "Liar's Loans." The deceptive practices were not disclosed to investors who purchased securities based on these loans, as required by market regulations and contractual obligations. Finally, mortgage fraud was clustered in economically fragile areas before the crisis and contributed to the prolonged deterioration during the Great Recession.

The empirical research has focused on directly observing fraud, and estimating the effects of fraud on delinquency at the loan level. However, we would also expect fraud to cause increased losses in foreclosure because most forms of fraud resulted in concealing increases in borrower leverage. The analysis in this paper fills this gap by 1) Accounting for the amount of losses to foreclosure in this market due to no/low documentation Liar's Loans, and 2) Estimating what portion of these losses can be considered excess from the perspective of the investor. Losses are considered "excess" if they are greater than those which would have occurred if the loan quality information disclosed to investors had been accurate, rather than fraudulent.

Fraud is defined as deception or misrepresentation with the intended to result in financial or personal gain. The term fraud is used in this paper in the broader economic sense, rather than the narrow legal sense. Fraud is used to refer to the economics of deception and trickery, rather than trades based on mutually beneficial gains. The term as used here should not be seen as having any legal significance. That being said, much of what occurred in this market was in fact illegal. These fraudulent practices have led to numerous lawsuits and Department of Justice settlements, but few prison sentences. Although their is no direcrt evidence of intent in the dataset, existing research has shown that the relevant parties in this market had the information to be adequately aware of misrepresentation, as well as the incentives to profit from deception (Griffin and Maturana, 2014*b*). Therefore fraud is the most accurate term to describe the practices in this market.

The private label, originate to distribute supply chain consisted of institutions which originated mortgages and sold these loans to trustees. The trustees then packaged the mortgages into securities, obtained ratings from ratings agencies, and sold the securities to investors. Losses in these securities were at the epicenter of the financial crisis of 2007-2008. A substantial body of research has documented a high incidence of mortgage fraud in the loans used as collateral for these securities. For example, as early as 2004 the FBI warned of an epidemic of mortgage fraud which could cause a financial crisis (Black, 2013). Also, the Financial Crisis Inquiry Commision concluded that a "systemic breakdown in accountability and ethics" was an essential cause of the crisis (Commission, 2011).

Executives at institutions that originated loans to be securitized in this market had perverse incentives to increase short-term profits based on the volume of loans originated, rather than the quality of loans. Executives were able to receive large bonus compensation for short term gains, for example through stock options that were not required to be paid back if the firm went bankrupt.[4] Fraud was particularly useful for increasing short-term revenues because toxic loans tended to have high initial fees attached to them. Similar to problems in

[4]Perverse incentives due to extreme bonus compensation were not limited to this market. They were a consistent feature of the expansion of the financial system following deregulation (Crotty, 2009).

the S&L crisis, this allowed originators to report high fee revenue before losses occurred (Black, 2013). Additionally, originating institutions could sell riskier loans to be securitized for a higher price than safer loans (Taub, 2014).

That being said, many of the originators still held a large portion of the toxic loans in their portfolio, and went bankrupt as a result. The pattern of extreme executive compensation, despite the failure of their firms, could reasonably be described as "looting." Looting occurs when owners or executives have limited liability for a firm, and maximize short-term pay-outs at the expense of the long run health of their firm resulting in bankruptcy. Looting has been described as bankruptcy for profit. (Akerlof and Romer, 1993). This pattern of looting is significant for macroprudential regulation because "skin in the game" rules that require institutions to hold a portion of the mortgages they originated in their portfolio would not have prevented fraud. These institutions had substantial skin in the game which caused their failure. However, their executives did not. Fraud prevention would likely have required increased monitoring of institutions, limits to extreme compensation packages, and criminal prosecution of top executives (Black, 2013).

These perverse incentives led originators to increase loan volume through the systematic abandonment of underwriting standards, or the outright falsification of documents. The common effect of these fraudulent practices was for loan officers to conceal increases in leverage or risk in order to qualify borrowers for larger loans than they would have been able to otherwise obtain. A recent set of empirical papers has directly measured a high incidence of a wide variety of types of mortgage fraud. These forms of fraud include income overstatement, asset overstatement, unreported second liens, misreported owner occupancy status, and appraisal inflation (Ben-David, 2011; Garmaise, 2015; Griffin and Maturana, 2014*b*; Jiang, Nelson and Vytlacil, 2014; Keys et al., 2010; Piskorski, Seru and Witkin, 2013). For example, using conservative measures Griffin and Maturana (2014*b*) find that 48% of loans contain at least one of three relatively easy to quantify forms of fraud: appraisal inflation, unreported second liens, and misreported owner occupancy status. They find that loans with one of these forms of fraud were 51% more likely to become delinquent.

The focus on no/low documentation loans in this study is meaningful because these loans were so notoriously fraudulent that they were colloquially known within the industry as "Liar's Loans." To be sure, at the time, originating no/low documentation mortgages was not prohibited as long as the stated income or assets were accurate. However, as the colloquial name indicates, these loans were not used to accurately state borrower financial characteristics. Indeed, loan officers often coached borrowers to falsely state their information, or falsified borrower documents without the borrower's knowledge.[5] As a result, these loans

[5]For example, Omar Khan, a loan officer at Ameriquest/Argent, stated, "Every closing was a bait and switch, because you could never get them to the table if you were honest." He further elaborated, "There were instances where the borrower felt uncomfortable about signing the stated income letter, because they didn't want to lie, and the stated income letter would be filled out later on by the processing staff" [*National Credit Union Administration Board v. Wells Fargo Bank, National Association*, 2014]. This anecdote is supported by an

performed particularly poorly. For example, Jiang, Nelson and Vytlacil (2014) estimated the effects of income overstatement on delinquency rates in Liar's Loans, and showed that the delinquency rate for these loans is 5-8 percentage points higher than the full documentation control group.[6] Most forms of Liar's Loans have now been prohibited.

This body of research has also shown that these forms of fraud were systematically concealed from investors who purchased securities based on these loans. For example, Piskorski, Seru and Witkin (2013) found that a "significant degree of misrepresentation exists *across all* reputable intermediaries involved in the sale of mortgages," [emphasis in original]. The sale of loans that were originated with fraudulent practices, or simply negligent underwriting, typically violated market regulations and contractual obligations. These rules require the accurate disclosure of loan quality; however, these practices obviously were not disclosed.[7] All major trustees have had numerous lawsuits initiated against them.[8] Forensic auditing has found that in some cases as high as 99% of the loans in an issuance were in violation of underwriting practices stated in offering documents. One court described the problem thus: "to accept that the Trustee was unaware of...reports and investigations [regarding underwriter and servicer misconduct] would require the court to 'find that responsible officers of Defendants had been living under a rock"' and that "[i]f the Trustee was indeed 'living under a rock,' it had no right to do so given it's role and responsibilities" (Galdston, Kaplan and Gilmore, 2014). The estimate of excess losses is significant from the perspective of the investors. The estimate shows on average

FBI study, which found that 80% of fraud cases involved "collusion or collaboration" with industry insiders based on investigations and fraud reports (FBI, 2007).

[6] However, the authors emphasize that this should be seen as a conservative lower bound, because the identifying assumption is that the full documentation control group is free of fraud.

[7] The typical offering documents included prospectus supplements which described the quality of collateral underyling the securities. These documents tended to include boilerplate language similar to, "Wells Fargo Bank's underwriting standards are applied by or on behalf of the Wells Fargo Bank to evaluate the applicant's credit standing and the ability to repay the loan, as well as the value and adequacy of the mortgaged properties collateral" *[General Retirement System of the City of Detroit v. Wells Fargo et al*, 2009]. If the trustee discovered a breach of these representations and warranties, such as falsification of borrower financial characteristics, violations of assurances that loans were originated following proper underwriting standards, or that the appraisal value for the collateral was inflated, the "trustee must notify the appropriate parties and take steps to enforce the responsible parties obligation to cure, substitute, or repurchase the defective mortgage loans" *[National Credit Union Administration Board v. Wells Fargo Bank, National Association*, 2014]. It should be noted that origination practices that could be argued were simply negligent or dubious, but did not involve outright falsfication, were still fraudulent because they violated the representations made in offering documents.

[8] An older list of 58 lawsuits filed between 2008-2012 can be found in the appendix to Piskorski, Seru and Witkin (2013). However, this list is not exhaustive, as the 2009 class action lawsuit used in this paper was not on the list (*General Retirement System of the City of Detroit v. Wells Fargo et al*, 2009). In addition, several similar lawsuits have been filed for violations of the False Claims Act or the Financial Institutions Reform, Recovery and Enforcement Act (FIRREA), for actions such as misrepresenting the quality of loans to entities which insured these loans. A list of 31 lawsuits can be found at: `http://www.buckleysandler.com/uploads/1082/doc/Recent-FIRREA-Cases_BuckleySandler-LLP_v20.pdf`. Accessed August 12th, 2015.

how much more the fraudulent loans used as collateral for these securities lost in foreclosure than if the information disclosed about them was accurate rather than misrepresented.

In contrast to the problems with originating institutions that could reasonably be described as looting, the problems in the market for securities based on these loans are more accurately described as a "market for lemons." The term "lemon" refers to a car which is poor quality, or more generally to any product that is poor quality. A market for lemons is a market where good and bad quality products are sold, but where the buyers cannot know beforehand whether they are buying a good or bad product. In these markets bad products tend to push out good products because good and bad products must sell at the same price. Over the course of the housing bubble, it is clear that bad practices in this market had pushed good practices out because these problems were common to all major institutions involved in the sale of these securities (Akerlof, 1970).

As of writing, the empirical papers on mortgage fraud have primarily focused on directly observing the incidence of fraud, and constructing loan level estimates of the effects of fraud on delinquency. However, we would also expect the concealed leverage and risk to cause these loans to lose more in foreclosure than non-fraudulent loans. Ben-David (2011) provides a simple illustration of how fraud concealed increases in borrower leverage using the example of appraisal inflation in the 2006 sale of a condo in Chicago. The condo was worth $235,000, but the builder was willing to inflate the price to $255,000 and return the extra cash to the buyer at the closing table. The buyer could then use the extra $20,000 as a down payment for a mortgage with a loan-to-value ratio of just under 95%. However, the true loan-to-value ratio was 100% because none of the borrower's own money was actually used for the down payment.[9] Due to this hidden increase in leverage, the loan would also be expected to lose more in foreclosure. This paper builds on the existing literature by estimating total excess losses for the entire market.

The estimates in this paper are also relevant for research that has shown that the geographic areas with high levels of fraud performed poorly during the Great Recession. These estimates of losses to foreclosure provide a quantitative description of one of the mechanisms that caused this poor performance. For example, Mian and Sufi (2015) construct a measure of fraudulent income overstatement on mortgage applications at the ZIP code level.[10] They find that high income overstatement ZIP codes performed significantly worse with higher default rates, negative income growth, increased poverty, and increased

[9] Alternatively, in some cases the buyer walked away with the money, used it to finance remodelings, or even to buy a new Mini-Cooper sports car in one instance. Also, loan originators often pocketed the extra money through high origination fees.

[10] They construct this measure as the difference in the annualized growth of income reported to the IRS, and reported on mortgage applications under the Home Mortgage Disclosure Act (HMDA). They find that the housing bubble period from 2002-2005 was unique in that the growth of income on mortgage applications reported in HMDA data substantially outpaced that reported on IRS documents, while in past periods the ratio of growth in income was constant. They find that this was driven by fraudulent income overstatement in the private label RMBS market.

unemployment. Additionally, Griffin and Maturana (2014*a*) find that areas with higher concentrations of originators who misreported mortgage information experienced a 75% larger relative increase in house prices from 2003 to 2006, and a 90% larger relative decrease from 2007-2012. The estimates of total and excess losses to foreclosure produced in this paper are significant for understanding the poor performance of these areas. Research has shown that foreclosures have large negative externalities which cause unnecesary destruction of wealth for everyone in a neighborhood. The large number of foreclosures that occurred during the financial crisis and Great Recession caused homes to be sold in a fire sale that depressed values for all houses in the neighborhood. The neighborhood wide reduction in house prices impaired all household balance sheets in an area, reducing aggregate demand. Research has shown that the causal effects of foreclosures during the financial crisis and Great Recession were responsible for roughly one-third of the decline in house prices, one-fifth of the decline in residential investment, and one-fifth of the decline in auto-sales (Mian, Sufi and Trebbi, 2014).

3 Research Design

The research design section is organized into three parts. The first part presents the data description, the second presents the identification strategy and regression model, and the third discusses data-driven refinements for the control group. Refinements are necessary for the full documentation control group because the empirical literature has shown that full documentation loans in the private label RMBS market also had a high incidence of fraud. This contamination would cause comparisons based on the unrefined control group to understate the true effects of fraud on excess losses. Refinements to reduce the incidence of fraud in the full documentation control group are made using qualitative data from lawsuit documents, measures of high fraud ZIP codes, and and regression discontinuity models from the empirical literature.

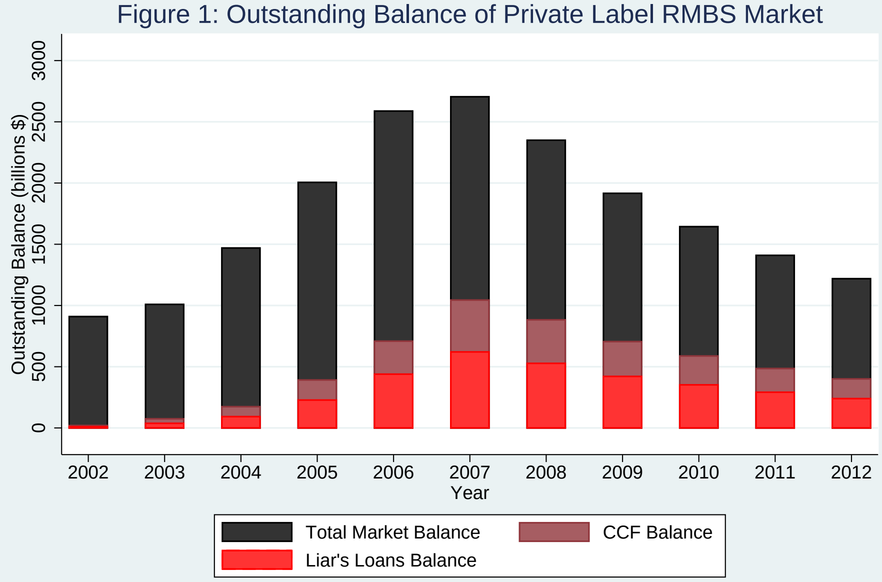
3.1 Data Description

The sample of loans used in this study comes from the Columbia Collateral File (CCF). The CCF is a large loan-level panel dataset that includes all loans used as collateral in private label RMBS for which Wells Fargo is a trustee. The data contains monthly observations for 139 variables that include measures such as loan characteristics and performance. The data begins in December 2006, which makes 2007 the first year for which complete data is available. In December 2007, the CCF contained roughly 4.2 million total loans; 2.4 million of these loans, or 58%, were Liar's Loans. By 2012 the number of loans in the dataset had fallen to roughly 1.8 million. This is largely due to the 1.5 million completed foreclosures that occurred.

Figure 1 shows the yearly outstanding balance of the the entire private label market, the CCF, and Liar's Loans in the CCF from 2002-2012. The private label market grew rapidly from 2002 to 2007, almost tripling in value. After peaking at an outstanding balance of $2.7 trillion in 2007, the market experienced severe losses and decline rapidly. The CCF was not a substantial portion of the market until 2005. However, it grew rapidly to account for just under 40% of market share in 2007 at an outstanding balance of $1.05 trillion.

Descriptions of fraud suggest that the intensity of fraud increased through time peaking roughly from 2005-2007. Liar's Loans have been reported to be particularly bad in this time period. The growth of the share of Liar's Loans in the CCF mirrors this pattern. In 2003 the share was 40% of loans in the CCF. The share grew rapidly to peak at two-thirds in 2007. The share has remained high at about 60% from 2007-2012 (SIFMA, 2015).

Figure 1: Outstanding Balance of Private Label RMBS Market



Data for oustanding balance of entire private label RMBS market comes from SIFMA.

The CCF data from 2007-2012 appears to be broadly representative of the entire market. In general, the data accounts for a substantial portion of the entire market and mirrors the growth of the market. Also, the summary statistics of observable risk measures are similar to those in Griffin and Maturana (2014*b*) and Piskorski, Seru and Witkin (2013). The dataset also contains loans originated by roughly 2000 different institutions.[11] However, there is also some reason to believe that the loans in the CCF performed better than average for the market. Wells Fargo was not found to be one of the ten originators with the highest incidence of fraud by Griffin and Maturana (2014*b*). This is corroborated by anecdotal reporting that the subprime origination practices at Wells Fargo

[11]There were approximately 7000-8000 entries for originator names in the CCF. However, redundancies in originator names occur across numerous dimensions such as capitalization, slight variation in name, spacing, etc. Therefore the actual size of the list is likely closer to 2000 originators.

were not as bad as for other institutions in the market. This led Wells Fargo to emerge from the crisis in a much better position than many other financial institutions.[12] Additionally, Wells Fargo has been the subject of fewer lawsuits than many other institutions.[13] Therefore, to the extent that fraudulent practices were less prevalent in the loans for which Wells Fargo was a trustee, the estimate of total and excess losses in this paper may understate losses to fraud in the entire market.

The main risk measures in this dataset are the FICO credit score and the loan-to-value (LTV) ratio. The LTV ratio is the ratio of the original loan balance to the appraisal value of the home and is a measure of the amount of leverage for a given mortgage. The LTV ratio measures the amount of equity in a home which serves as a cushion to absorb house price declines. The FICO credit score is an index of creditworthiness that measures the borrower's chance of default over the next two years. A higher credit score indicates a less risky borrower. The score is based on the amount of debt a borrower currently owes, the borrower's payment history, types of credit in use, the length of credit history, and new credit.

The sample of loans from this dataset is restricted to all mortgages that are 1st lien, owner occupied, originated between 2002-2008, with loan-to-value ratios between 70 and 100, FICO credit scores between 300 and 850, balances greater than $30,000, and for which there are complete data. The pooled sample is built by merging the December data to provide a retrospective snap shot of the year. After these restrictions, the final 2007-2012 pooled sample includes slightly over 7 million loan-year observations. The sample also includes roughly 700,000 of the 1.5 million unique foreclosures. A large portion of foreclosures are typically dropped the month after the foreclosure sale is recorded, so dropped foreclosures are merged back into the December observations.

To my knowledge this study is the first to use this dataset in the context of measuring the effects of fraud on losses to foreclosure. However, the sample is compiled from trustee reports so it is most similar to the data used in Griffin and Maturana (2014*b*) and Piskorski, Seru and Witkin (2013). The main advantage of this data relative to others used in the literature is that this data contains detailed information on losses to foreclosure. It is not clear if information on losses to foreclosure is availale in the other data sources used in the empirical literature. However, no other paper has measured losses in foreclosure due to fraud.

The ideal dataset for comprehensively estimating the total effects of fraud would be a loan-level panel set which included measures that recorded whether a loan was fraudulent or not, what type of fraud, and how intense the fraud was (i.e., whether income was overstated 5% or 50%). The obvious main disadvantage of data from the CCF is that it does not directly measure fraud in this manner. Others have been able to directly measure certain easy to quan-

[12]For example, see `http://www.economist.com/news/finance-and-economics/21586295-big-winner-financial-crisis-riding-high`

[13]For example, Wells Fargo appears far fewer times than other institutions on the two lists of lawsuits in footnote 8.

tify types of fraud by matching loan-level records with data from other sources such as credit bureau records. However, these data come from large proprietary datasets which as of writing I do not have access to.

To address the limitation of not being able to directly observe all forms of fraud, I restrict the analysis to only estimating the effects of fraud on losses to foreclosure in no/low documentation loans. These loans were known colloquially within the industry as "Liar's Loans" because they were notoriously fraudulent. These loans were overwhelmingly used to overstate borrower income or assets. Therefore the estimates produced in this paper do not represent exhaustive estimates of losses due to all forms of fraud, but are limited to only measuring losses based on lack of documentation. Additionally, addressing this limitation also requires refinements to the full documentation control group to reduce the incidence of fraud. These refinements are detailed in the sub-section 3.3.

3.2 Identification Strategy and Regression Model

Fraudulent loans are expected to cause increased losses to foreclosure because most forms of fraud result in concealing borrower leverage and risk. This analysis identifies the causal effects of fraud on excess losses to foreclosure by comparing losses for loans in the no/low documentation treatment group with losses for loans with similar risk measures in a refined full documentation control group. Excess losses in the treatment group which cannot be explained by observable risk measures are consistent with the causal effects of fraud.

The mean differences in losses to foreclosure between treatment and control groups can be decomposed into two portions.

$E[L|D_i = 1] - E[L|D_i = 0] = \{P(FC|D_i = 1) - P(FC|D_i = 0)\}E[L|FC, D_i = 1] + \{E[L|FC, D_i = 1] - E[L|FC, D_i = 0]P(FC|D_i = 0)$,

where L =loss in foreclosure, FC = foreclosure, and D_i is an indicator variable coded 1 for the treatment group. The first of these terms is the increase in losses due to the extra foreclosures caused by fraud. The second term is the increase in losses for Liar's Loans conditional on foreclosure (Angrist and Pischke, 2008).[14]

I use a simple linear regression models to estimate these effects in two steps. The regression model is:

$y_{izt} = \alpha_z + \gamma_t + \beta_0 + \beta_1 * D_i + \Lambda * X_i + \epsilon_i$,

where y_i is one of four outcome variables, D_i is the binary treatment variable, X_i is a vector of controls, α_z is a set of ZIP code level fixed effects, and γ_t are loan-year observation fixed effects. Standard errors are clustered at the ZIP code level for all models. This model is run for the pooled sample of loans; however, the results are robust to running the model for each year seperately.

The first set of regressions measures estimates the increase in the foreclosure rate using an indicator variable coded 1 for loans that were foreclosed on during a year. The second set of regressions measures the increase in losses in dollars

[14]In addition to conditioning on foreclosure and treatment status, these means also need to be conditioned on appropriate controls. These subscripts have been omitted to facilitate ease of presentation.

using data from the variable loss on liquidated property. This variable likely includes all home forfeiture actions more broadly, such as short sales or deeds in lieu. These actions are all substantially similar to foreclosure because they require loss of the home. I also estimate extra delinquencies using an indicator variable coded 1 for loans that were delinquent at least once during the year. Finally, I estimate losses as a share of the original balance. This helps normalize losses to foreclosure to help ensure that the dollar value estimates are accurate. Foreclosure and delinquency rates are estimated in the full pooled sample, while losses are estimated conditional on foreclosure.

The set of controls includes risk measures, loan type, loan purpose, origination years, and original balance. The principal risk measures employed are the loan-to-value (LTV) ratio and FICO score. A set of indicators for low, medium, and high LTVs are used for the regressions. Low LTVs are those with LTVs of 80 and under, which is the traditional cut off for the classic mortgage. High LTVs are those with LTVs of 95 or higher because this is a common cut-off for inclusion into RMBS pools. LTVs between 80 to 95 are considered medium leverage mortgages.

Indicators are also included for FICO credit scores. The OCC Mortgage Metrics report defines subprime loans as those with FICO scores less than 620, alt-A loans as those with FICO scores between 620 and 660, and prime loans as those with FICO scores above 660. In addition an indicator is also included for FICOs greater than 760, which is the cut off for the "FICO High Achievers" list.[15]

Indicator variables for loan type and purpose are also included in the regressions as well. The dataset has two broad types of mortgages: fixed rate and adjustable. Fixed rate mortgages are typically considered the least risky, while adjustable rate are considered higher risk. Finally, indicator variables for origination year and observation year are also included.

Formally, identification depends on $E[\epsilon_i|D_i, X_i, \alpha_z, \gamma_t] = 0$. This condition should be largely satisfied because the highly detailed micro data allows for fine-grained controls for risk measures, geographic shocks, or different shocks by year. Comparing loans with similar risk measures, in the same ZIP codes, and within the same years should eliminate selection bias on observables. In addition, I conduct the Oster (2014) robustness test in section 5 to assess the stability of estimated coefficients due to selection on unobservables.

There are also two known problems with this identification strategy. These problems would both cause the estimates to understate the true causal effects of fraud on losses to foreclosure. The first problem is that estimating excess losses conditional on foreclosure introduces the conditional-on-positive selection bias. The estimate of excess losses conditional on foreclosure can be decomposed into a causal effect and a selection bias. Selection bias arises due to fraud changing the composition of those who are foreclosed on (Angrist and Pischke, 2008). In this case, the bias likely understates the true effects of fraud because fraud

[15] This definition comes from myfico.com. Accessed 6-25-2015 from: `http://ficoforums.myfico.com/t5/Understanding-FICO-Scoring/Expanded-quot-FICO-High-Achievers-quot-scores-of-760-and-above/td-p/111525`.

lowers the threshold for those that are foreclosed on in the treatment group. At the margin, the set of foreclosed loans in the Liar's Loans group should therefore be larger and contain more borrowers who were less risky than the full documentation group. This selection bias would understate average losses. Thought of slightly differently, the set of borrower's who were selected into foreclosure in the full documentation group were more risky on average ex-ante because they ended up in foreclosure despite having better loans. The inclusion of appropriate controls for risk to some extent should mitigate some of this selection bias, but it is unlikely to completely eliminate it. That being said, the estimation of the effects of fraud on delinquency and foreclosure rates are unaffected by this bias and still have a causal interpretation. To the extent that risk controls do not mitigate this selection bias, the estimates of losses conditional on foreclosure in this paper would understate the true causal effects of fraud.

The second problem with this identification strategy is the presence of fraud in the full documentation loan control group. This problem has been well documented in the existing research and would cause the estimate of excess losses to understate the true effects of fraud (Jiang, Nelson and Vytlacil, 2014). For example, the widespread incidence of fraud in full documentation loans in this market was confirmed by Griffin and Maturana (2014*b*). They found that roughly half of full documentation loans contained at least one of three easy to measure types of fraud: appraisal overstatement, misreported owner occupancy status, or unreported second liens. Therefore, refinements to the control group to remove full documentation loans with a high probability of fraud are necessary and will be described in the next section. Surprisingly, Griffin and Maturana (2014*b*) also found a similar incidence of fraud between full documentation and Liar's Loans for these measures. However, Griffin and Maturana (2014*b*) were not able to estimate differences in income or asset overstatement which is likely the main dimension of fraud on which no/low and full documentation loans differ. Therefore, the comparison of these loans should still provide an estimate of meaningful differences in fraud provided that refinements are made to the control group. To the extent that the refinements do not completely purge fraud from the control group, we would also expect the estimates in this paper to underestimate the true causal effects of fraud. For these reasons, the estimates produced in this paper are best interpreted as a conservative lower bound for the true causal effects.

3.3 Refinements to the Control Group

I make two refinements to the control group to remove loans with a higher probability of containing fraud. First, I use qualitative information from lawsuit documents concerning the actual loans in the dataset to remove loans originated by institutions notorious for employing fraudulent practices. Second, I remove loans from ZIP codes with high levels of fradulent income overstatement on mortgage applications. I then use regression discontinuity models based on those in the empirical literature to confirm the presence of fraud in the control group, and show that the refined control group is meaningfully freer of fraud than the unrefined control group.

The sample of loans used in this article is from the Columbia Collateral File (CCF) which includes all publicly available collateral files for RMBS for which Wells Fargo serves as a trustee. Wells Fargo has been sued at least twice for misrepresenting the qualities of these loans in offering documents. In 2011, Wells Fargo settled a class action law suit for approximately $125 million with several retirement funds that sustained large losses on RMBS purchased from Wells Fargo [*General Retirement System of the City of Detroit v. Wells Fargo et al*, 2009]. As of time of writing, Wells Fargo is also being sued by the National Credit Union Administration (NCUA) for severe losses on $2.4 billion in RMBS purchased by five credit unions, which caused the liquidation of the five institutions [*National Credit Union Administration Board v. Wells Fargo Bank, National Association*, 2014].

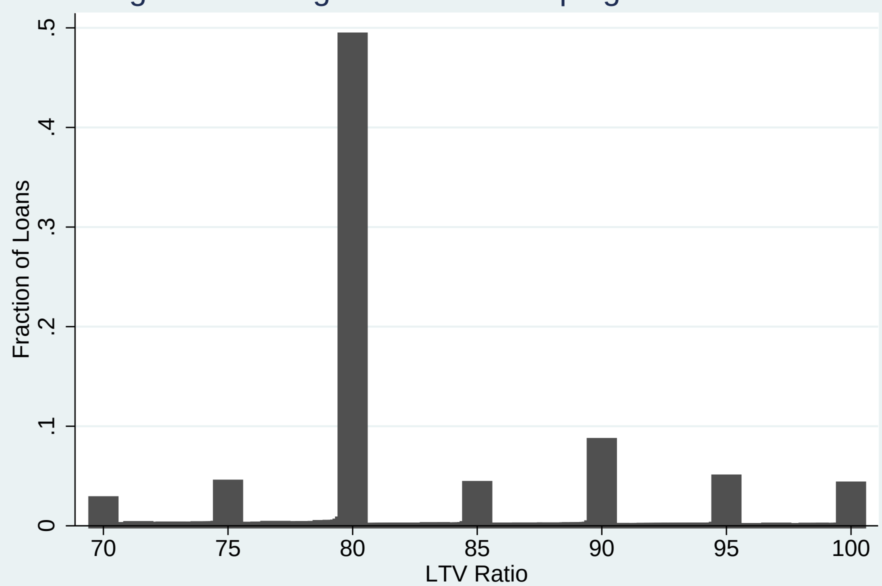
These lawsuits provide important qualitative information concerning the high incidence of fraudulent practices at particular loan originators, with a total of twenty-five institutions discussed in depth in both lawsuits. High fraud originators are one of 25 institutions whose fraudulent practices were described in depth in either lawsuit document, while low fraud originators are institutions who are not mentioned in either lawsuit document.[16] Even though the high fraud originators are only 25 institutions out of a possible list of approximately 2000 institutions, these originators were also some of the larger institutions and originated approximately half of the loans in the sample with data recorded for originator name, depending on year. While the study makes use of lawsuit documents which target Wells Fargo, this study should not be interpreted as singling out Wells Fargo for uniquely poor practices. Deceptive practices were common to all institutions in this market, and all trustees have had numerous lawsuits initiated against them. Moreover, as discussed above there is reason to believe that the practices at Wells Fargo may have been less fraudulent than average for this market.

Two regression discontinuity models based on loans clustering at LTV intervals of 5 are used to confirm fears of the presence of fraud in the unrefined full documentation control group, and that the refinements provide a control group more free of fraud. Griffin and Maturana (2014*b*) find that a large portion of loans in this market were discontinuously clustered at LTV intervals of 5 units (75, 80, 85, etc.) which can be seen in Figure 2 below. They find that appraisal overstatement was consistently higher for clustered loans, and that these loans consistently defaulted at a much higher rate. They conclude that this pattern is more consistent with appraiser's targeting home valuations given by loan officers

[16]The originators named in the NCUA lawsuit are: Ameriquest/Argent, Bank of America, Countrywide, Decision One, DLJ, First Franklin, Fremont, GreenPoint, Impac, Morgan Stanley Mortgage Capital, National City, New Century, Option One, Paul Financial, RBS/Greenwich Capital, WMC Mortgage Corp; and the originators named as defendants or named in testimony in the retirement fund lawsuit are: American Home Mortgage (named in testimony), Bank of America, Bear Stearns, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, Merrill Lynch, RBS/Greenwich Capital, UBS, and Wells Fargo.

than with a random pattern of mistakes.

Figure 2: Histogram of LTV Heaping at Intervals of 5



The first model measures excess losses at the LTV intervals. The regression discontinuity model measures the increase in negative outcomes for loans clustered at the LTV intervals of 5, which have been shown to have a higher incidence of fraud. The regression discontinuity model includes an indicator for clustered loans, and controls for a fourth degree polynomial of LTV. The model is:

$$Y_i = \alpha_z + \beta_0 + \beta_1 Z_0 + \beta_2 ltv + \beta_3 ltv^2 + \beta_4 ltv^3 + \beta_5 ltv^4 + \Gamma X_i + \epsilon_i,$$

where Z_0 is an indicator variable for loans with clustered ltv values, and the rest of the controls are the same as those used in the main regressions. The excess losses measured by the estimated coefficient for Z_0 are distinct from the excess losses presented as the main result. The coefficient for Z_0 measures excess losses for loans at the LTV interval compared to loans within the same documentation type not at the LTV interval, rather than compared to a fraud-free control group. Therefore, this is a useful tool to measure the incidence of fraud within a single documentation type, but not across types. Results for this test can be seen in Table 1 and Figure 3 below.

The second model based on this discontinuity is to use the McCrary (2008) heaping test for manipulation of the running variable. This test measures the threat to identification in regression discontinuity designs of agents strategically manipulating treatment status. The test first divides the data into a rough histogram based on the running variable, and then smooths the histogram on either side of the breakpoint being tested. Manipulation of treatment status would produce heaping at the breakpoint, which is measured as the log difference in the height of the smoothed polynomials fitted on either side of the breakpoint. This test is relevant to the current analysis because it is likely that a substantial portion of the heaping seen at LTV intervals of 5 comes from loan officers telling appraisers to target a specific valuation price that would produce the desired LTV ratio. The heaping test only allows a single breakpoint to be tested, so the data are recentered around the LTV intervals. The default bin size of 1 and bandwidth are used. Results for this test are presented in Table 1 and Figure 4 below.

Table 1: Results for Excess Losses and Heaping from Regression Discontinuity Models Based on LTV Clusters

	Excess Negative Outcomes		Excess Heaping	
	Loss/Orig Balance	Loss ($)	Log Difference	N
Full Doc				
Unrefined	0.00739***	2734.3***	3.24	296657
	(4.44)	(6.92)	(.003)	
High Fraud	0.0127**	3971.9***	3.65	66327
	(3.35)	(3.91)	(.008)	
Semi-Refined	-0.00241	1939.3	3.18	57769
	(-0.61)	(1.88)	(.007)	
Refined	-0.00557	1634.8	3.40	15379
	(-0.60)	(0.75)	(.014)	
No Doc				
Unrefined	0.0139***	5400.7***	3.43	374910
	(9.29)	(11.08)	(.003)	
High Fraud	0.0152***	6289.2***	3.64	90430
	(5.16)	(5.58)	(.007)	
Semi-Refined	0.0101***	4958.9***	3.41	108424
	(3.21)	(5.74)	(.005)	
Refined	0.0208***	5764.6**	3.39	22140
	(3.59)	(2.59)	(.011)	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

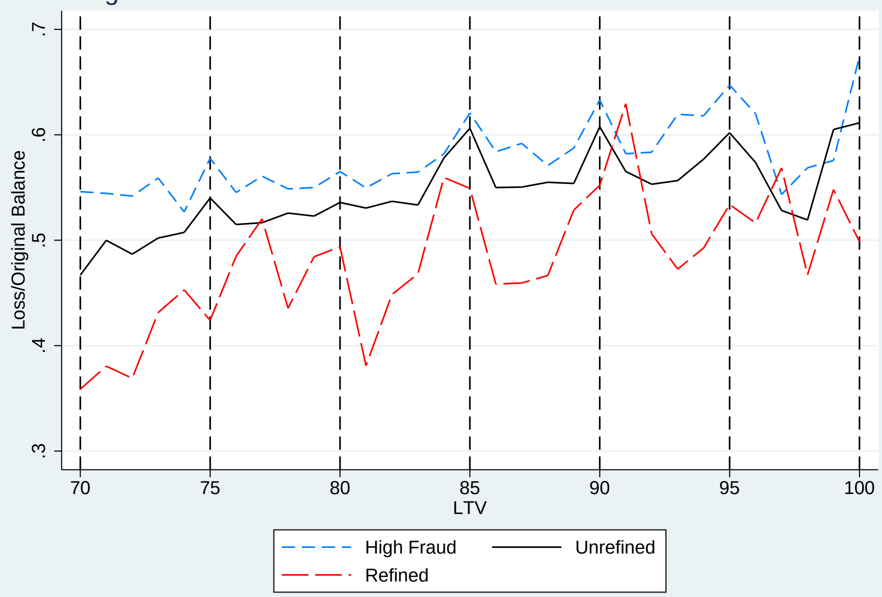
This table presents results from regression discontinuity models based on loan clustering at LTV intervals of 5, by documentation type and level of refinement. Columns 1 and 2 present results for excess losses, with t-statistics in parentheses. Column 3 presents results from the McCrary heaping test (log-difference) with standard errors in parentheses. Column 4 presents the total number of loans (N) by level of refinement. The unrefined group uses all loans within a documentation type. The high fraud group uses all loans from high fraud originators within a documentation type. The semi-refined group removes all loans from high fraud originators. The fully refined group also removes all loans from high fraudulent income overstatement zip codes.

Table 1 presents results from the two tests. Columns 1 and 2 show results for excess losses, while column 3 presents results from the McCrary test. T-statistics are reported in parentheses for excess losses while standard errors are reported in parentheses for the heaping test. The table compares regression discontinuity results for the unrefined full documentation control group, full documentation loans from high fraud originators, the semi-refined full documentation control group which removes full documentation loans from high fraud originators, and the fully refined full documentation control group which removes loans from high fraud originators as well as those originated in ZIP codes above the median level of fraudulent inome overstatement. These groups are also compared for no/low documentation loans. The basic findings in this table are 1) the unrefined sample of full documentation loans shows measures consistent with fraud, while 2) both semi- and fully-refined full documentation control groups exhibit fewer measures associated with fraud than the full documentation control group. Additionally, measures consistent with fraud are found for both semi- and fully-refined no/low documentation groups, so it is unlikely that the null finding for semi- and fully-refined full documentation loans is spurious.

The test for excess losses showed that unrefined full documentation and high fraud full documentation loans clustered at LTV intervals of five exhibited excess losses, relative to loans in these groups not clustered at LTV intervals. Excess losses for these groups ranged from roughly $3,000-$4,000 dollars. Unrefined and high fraud no documentation loans also showed excess losses which were larger than those estimated for full documentation loans in these categories by roughly $2500. In contrast to unrefined and high fraud full documentation loans, semi-refined and fully refined full documentation groups did not exhibit statistically significant excess losses. However, semi-refined and fully-refined no documentation groups did exhibit excess losses similar to unrefined and high fraud groups. This suggests that the null finding for semi- and fully-refined full documentation groups is not spurious.

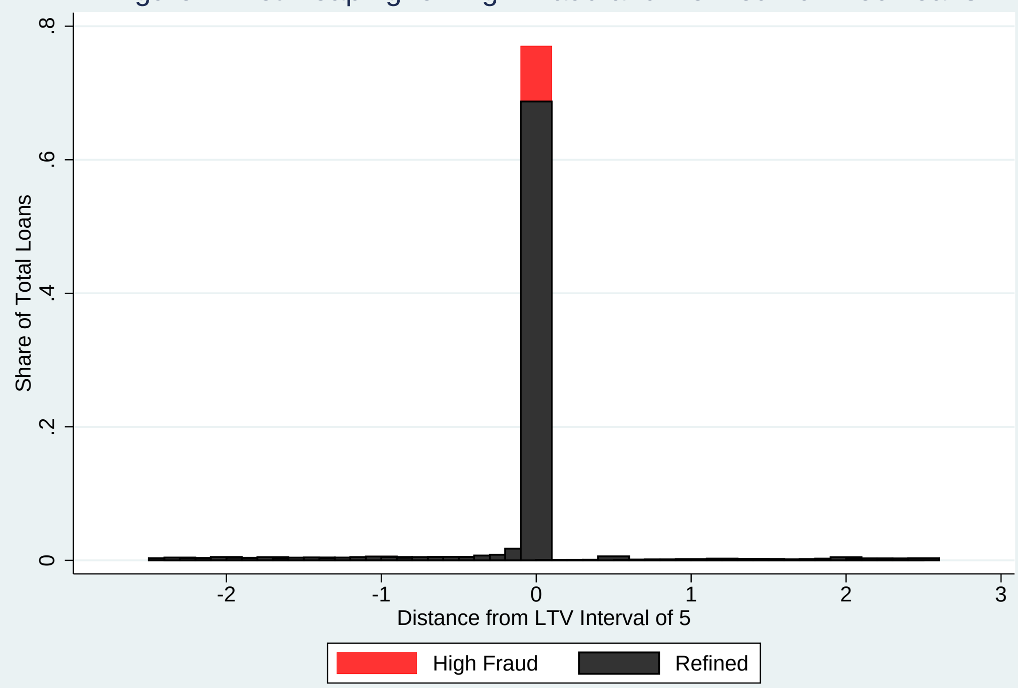
The results for the excess losses for loans clustered at LTV intervals can also be seen in Figure 3. Figure 1 displays excess losses for the unrefined control group, high fraud full documentation loans, and the fully refined control group. The graph shows that excess losses for the unrefined control group and high fraud full documentation loans consistently reach local maximums at the LTV intervals of five, shown with reference lines. For these two groups, the local spikes all consistently coincide with the LTV intervals. However, this pattern does not occur for the refined control group. The spikes in excess losses for the refined control group almost all occur away from the LTV intervals of 5, with approximately equal amounts occuring above as below the LTV intervals. This suggests that the pattern of losses for the refined control group is more random, while the pattern for the other two groups is not.

Figure 3: Excess Losses at LTV Intervals of Five for Full Doc Loans



The McCrary tests in Table 1 showed significant heaping for all groups. However, high fraud loans showed consistently more heaping than any other group. When considered with the positive excess losses, this suggests that the full documentation loans from high fraud originators are appropriate for removing from the control group. The semi- and fully-refined groups also still exhibited excess heaping. While this heaping was not associated with statistically significant excess losses, this raises some concern that fraud has not been completely purged from the control group. To the extent that some fraud remains in the fully-refined control group, the estimates in this paper would understate the true effects of fraud. Figure 2 shows heaping for high fraud and fully refined groups. The data is centered around the LTV intervals to facilitate visual comparison. As can be seen, both groups exhibit a subtantial amount of heaping. That being said, the refined group exhibits less heaping than the high fraud group.

Figure 4: Net Heaping for High Fraud and Refined Full Doc Loans



The final table in this section shows the distribution of covariates between the Liar's Loans treatment and fully-refined full documentation control groups to assess any possible observable selection bias. Table 2 is divided into three panels. Panel A shows mean loan information including the original loan balance, LTV and FICO score. Panel B presents the distribution of risk measures, loan type, and loan purpose between groups. Finally Panel C presents loan performance information. The basic finding in this table is that the control group consistently has worse observable risk measures than the treatment group. To the extent that this selection is not entirely mitigated by the risk controls, we would expect the estimates in this paper to underestimate the true effects of fraud.

In panel A, we see that the control group has a slightly lower original balance than the treatment group. This is consistent with the slightly riskier average measures for the control group. The control group mean FICO score was roughly 30 points lower than that for the treatment group, while the LTV was 3 percentage points higher. Panel A also shows the number of loans in the treatment and control group. The refinements removed a substantial portion of loans from the control group. Removing loans from high fraud originators caused the largest drop in loans because only roughly half of the data contained originator names.[17] Removing loans from ZIP codes above the median fraudulent income

[17] While only half of the data contains originator names, all observations contain data for the current servicer of the loan. As will be more fully discussed in the robustness section, the

Table 2: Sample Description

Panel A: Loan Information (mean)		
	Treatment	Control
Original Balance ($)	324,749	274,638
Loan-to-Value	80.9	83.5
FICO Score	684.7	652.4
N	3,695,068	204,529

Panel B: Distribution of Risk Measures, Loan Type, and Purpose (%)		
	Treatment	Control
FICO Score		
Sub Prime	12.5	36.4
Alt-A	20.4	20.7
Prime	55.2	31.5
High Achiever	11.9	11.4
Loan-to-Value		
LTV <= 80	80.3	61.5
80 < LTV <= 95	13.5	24.1
95 <= LTV	6.3	14.5
Loan Type		
Fixed Rate	32.7	49.2
Adjustable Rate	67.3	50.8
Loan Purpose		
Purchase	53.0	40.5
Refinace	13.9	16.1
Cash-out Refinance	33.1	43.4

Panel C: Loan Performance		
	Treatment	Control
Delinquency Rate (%)	46.8	38.0
Foreclosure Rate (%)	10.2	7.5
Mean Loss in Foreclosure ($))	176,315	97,675
Loss/Original Balance (%)	57.8	50.3
LTV if Foreclosed (mean)	81.6	84.8

overstatement also removed a large portion of loans. Only roughly one-third of the loans in the CCF were originated in ZIP codes below the median level of income overstatement. However, there are still over 200,000 loans left so lack of statistical power should not be a problem.

Panel B shows the distribution of LTV ratios, FICO scores, loan purpose, and loan type between these groups. The control group had a significantly larger proportion of subprime FICO scores than the treatment group, which had roughly 67% of loans with credit scores prime or higher. The treatment group also had 80% of loans with LTV ratios 80 or under. This is a high proportion of loans that should have had a large equity cushion to absorb house price declines of up to 20%. The treatment group also had less risky loan types and purposes. Cash-out refinances were notoriously abused during the housing bubble, and the treatment group includes fewer cash-out refinances. The treatment group does include more adjustable rate mortgages, which were riskier than fixed rate mortgages. However, on net, the treatment group has substantially better observable risk measures. Due to the better risk measures in the treatment group, if selection bias persists despite the inclusion of controls, we would expect this bias to understate the true effects of fraud.

The final panel shows loan performance statistics. The poor performance of these loans is without precedent in recent history. For example, the delinquency rate between 1995-2005 averaged roughly 2%, and peaked at 11% during the crisis. Despite having better observable risk measures, the treatment group had a delinquency rate almost 9 percentage points higher than the already high delinquency rate of the control group. This difference alone is almost the entire peak rate for all mortgages during the crisis. Additionally, the foreclosure rate was roughly 25% higher for the treatment group. These loans also lost a large amount in foreclosure at close to 60% of the original balance or $176,000. Combined with the roughly 80% mean LTV of foreclosed Liar's Loans, the average loss of close to 60% of the original balance implies that the value of the home must have declined by roughly 80% of the appraised home value. In contrast, the control group lost slightly less of the original balance despite having a higher mean LTV.

4 Main Results

Section 4 presents the main results for total and excess losses to foreclosure caused by fraudulent Liar's Loans. The main findings in this section are that total and excess losses in foreclosure due to fraud were substantial, prolonged, and concentrated in neighborhoods particularly poorly suited to bear the losses. Losses to foreclosure for the entire private label RMBS market totaled roughly $500 billion from 2007-2012. Roughly 70%, or $345 billion, of these losses are accounted for by losses in no/low documentation Liar's Loans. Of this $345

estimates in this paper are robust to including high fraud servicers in the high fraud originator measure to preserve some of the data.

billion, roughly $100 billion can be considered a conservative lower bound estimate for excess losses. This implies that excess losses in Liar's Loans alone account for 20% of total market losses. Fourty-four percent of total market losses occurred in ZIP codes above the 75th percentile of fraudlent income overstatement. These neighborhoods were already economically fragile before the financial crisis and experienced terrible economic performance throughout the Great Recession. The prolonged foreclosure crisis was a significant factor in explaining this poor performance.

The results in this section are presented in two tables and one figure. Table 3 presents estimates of excess foreclosures, delinquencies, and losses conditional on foreclosure. Table 4 uses these estimates to calculate total and excess losses at the level of the entire market. Finally, Figure 5 shows the distribution of these losses through time.

Table 3: Main Results: Excess Negative Outcomes for Liar's Loans in Pooled Sample

	No Controls	Some Controls	**Preferred**	Unrefined
Loss ($)	26083.4***	21290.1***	22912.3***	11112.8***
	(22.61)	(20.05)	(29.02)	(42.98)
Loss/Orig Balance	0.106***	0.0906***	0.0911***	0.0359***
	(20.43)	(18.47)	(28.27)	(42.84)
N	390289	390289	390289	671567
Foreclosure Rate (%	0.0269***	0.0290***	0.0209***	0.0175***
	(22.53)	(27.86)	(27.68)	(55.51)
Delinquency Rate (%)	0.0903***	0.128***	0.0980***	0.0812***
	(26.28)	(48.33)	(48.54)	(103.13)
N	3899597	3899597	3899597	7018803

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 shows the main results for excess foreclosures, delinquencies, and losses conditional on foreclosure for Liar's Loans in the pooled sample. The table presents results from regressions of the outcomes on the no/low documentation indicator, with 1) no controls, 2) risk controls only, 3) all controls, and 4) the unrefined full documentation control group with all controls. Specifications one to three move from least saturated to most saturated models, with the most saturated model being the preferred estimate. The unrefined specification is included to allow us to assess the the size of the effects of the refinements. Specification one regresses each outcome on the treatment indicator, and only controls for the size of the original balance. Specification 2 also includes sets of controls for the LTV ratio, FICO score, loan purpose, and loan type. Finally, specification three also includes ZIP code level fixed effects, indicators for origination year, and loan-year observation fixed effects.

All specifications in this table show statistically and economically significant results for all outcomes. The results are also reasonably consistent across specifications. The preferred estimate in this table shows that the conditional foreclosure rate was roughly 2.1 percentage points higher than that for the control group. This result implies that fraud caused a 30% relative increase in foreclosures compared to the control group foreclosure rate of 7.5%, or equivalently that roughly one-fifth of Liar's Loans foreclosures were excess. Excess losses conditional on foreclosure in dollar values for the preferred specification were just under $23,000. To the extent that the risk controls do not completely eliminate COP selection bias, this represents an underestimate of the true causal effects. However, the size of this estimate is plausible and consistent with descriptions of the size of the average fraud in the literature. In the example of appraisal inflation presented by Ben-David (2011), the price of the home was inflated $20,000. Excess losses as a share of the original balance for the preferred specification were 9 percentage points of the original balance. The average loss as a share of the original balance for the refined control group was 50%. This implies that Liar's Loans lost 20% more conditional on foreclosure than the control group average.

Excess foreclosures estimated for the unrefined control group are also consistent with those estimated for the refined group. The increase in the foreclosure rate for this specification was 1.75 percentage points, which is similar to that estimated for the refined model. Excess losses conditional on foreclosure were just under half as large as those estimated for the refined specification. The difference in losses suggests that the refinements did meaningfully reduce the incidence of fraud in the unrefined control group. This also helps to assess how sensitive the final results are to the refinements employed. As discussed in greater depth in the next section on robustness test, estimates from other alternative refinements fall in between estimates using fully-refined and unrefined control groups.

Excess delinquencies were also large and consistently averaged just under 10 percentage points across specifications. This increase is quite substantial at roughly 25% greater than the average delinquency rate of 38% for the refined control group. Additionally, the estimates of excess delinquencies are within the range of estimates in the existing research. The increase is slightly higher than the 5 - 8 percentage point increase reported by Jiang, Nelson and Vytlacil (2014) which was based on their unrefined full documentation control group. However, the increase in excess delinquencies was less than the 50% - 60% increase in the delinquency rates estimated by Piskorski, Seru and Witkin (2013) and Griffin and Maturana (2014*b*). These results were produced by directly observing fraud and are therefore the most credible in the literature. This suggests that the refinements made to the full documentation control group may not have completely eliminated the presence of fraud. That being said, the increase in excess losses to foreclosure estimated with the refined group was larger than this increase. This suggests that unrefined and refined estimates provide a reasonable bracket for the true effects, assuming that COP selection bias is mitigated by the inclusion of risk controls.

Table 4: Total and Excess Losses to Foreclosure for the Entire Private Label RMBS Market from 2007-2012

Panel A: Total Losses and Foreclosures		
	Full CCF	Entire Market
Foreclosed Balance (billions $)		
All Loans	$321.54	$892.95
Liar's Loans	$220.05	$611.10
Losses to Original Balance in Foreclosure (billions $)		
All Loans	$179.51	$498.51
Liar's Loans	$125.06	$347.30
Total Foreclosures		
All Loans	1,473,244	4,091,345
Liar's Loans	890,960	2,474,284
Panel B: Excess Losses and Foreclosures in Liar's Loans		
	Full CCF	Entire Market
Losses due to Extra Foreclosures (billions $)	$25.62	$71.16
Total Liar's Loans Excess Foreclosures	184,306	511,837
Average Loss in Foreclosure	$140,384	-
Excess Losses in Foreclosure (billions $)		
Unrefined	$7.85	$21.81
Refined	$16.19	$44.96
Total Excess Losses (billions $)		
Unrefined	**$33.50**	**$93.02**
Refined	**$41.86**	**$116.24**

Table 4 shows total and excess losses from 2007-2012 projected to the level of the entire market using the average CCF market share. Panel A shows total losses and foreclosures. The total foreclosed balance in the CCF was $321.5 billion, which implies a total market foreclosed balance of almost $900 billion. Over half of this foreclosed balance was not recovered through foreclosure auctions. Losses for Liar's Loans accounted for 70% of total losses, and 40% of the foreclosed balance. Raw numbers of foreclosures were also substantial at 1.5 million in the CCF, and 4 million for the entire market. In comparison, estimates of the total number of foreclosures for the financial crisis and Great Recession suggest that roughly 5 million foreclosures occurred, and an additional 5 million home forfeiture actions similar to foreclosures occurred.[18] Therefore, the CCF dataset accounts for roughly 15% of total home forfeiture actions that occurred, and the private label market accounts for roughly 40%.

Panel B presents the total amount of excess losses and foreclosures implied by the regression results, which are substantial. Excess losses due to extra foreclosures and excess losses conditional on foreclosure are presented seperately, as well as the total effect. To project the findings from the sample to the level of the full CCF, the average loss conditional on foreclosure for Liar's Loans in the full CCF is used, roughly $140,000. This is less than the sample average Liar's Loan loss of 180,000 largely because LTV ratios of less than 70 were omitted from the sample.[19]

Excess losses due to extra foreclosures is simply the number of excess foreclosures times the average loss in foreclosure. This is not presented seperately for refined and unrefined groups because the regression estimates implied similar amounts of excess foreclosures for these groups. Roughly 20% of Liar's Loans foreclosures were excess, which implies that over 500,000 Liar's Loans foreclosures at the level of the market were excess. The effect due to extra foreclosures totaled $71 billion for the market, which is where the bulk of excess losses occured. The effect due to loss conditional on foreclosure is the loss conditional in foreclosure times the number of non-excess Liar's Loans foreclosures. At the level of the market, the loss conditional on foreclosure effect ranged between $21-$45 billion. These results imply total losses ranging from $93-$112 billion for this market. Total excess losses account for 40% of total Liar's Loans losses, and 20% of total market losses. While these losses are quite substantial, it is worth re-emphasizing that they are best seen as a conservative lower bound.

[18] http://www.creditslips.org/creditslips/2013/10/foreclosure-crisis-update.html

[19] Excess losses for the market using the sample average loss of $180,000 total roughly $112-$135 billion for the unrefined and refined control groups respectively.

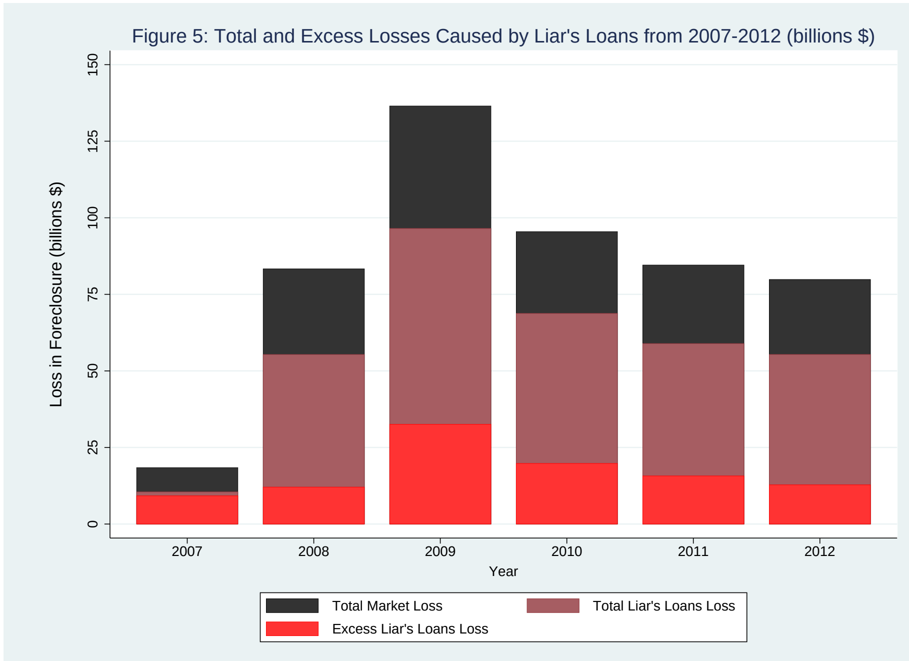


Figure 5 shows the level of total market losses, total Liar's Loans losses, and excess Liar's Loans losses for each year from 2007-2012. This figure is significant because it shows that the bulk of losses to foreclosure were substantially more prolonged than the financial crisis. The market panic had largely subsided by 2009. However there were over $125 billion in losses to foreclosure in 2009, and between $75-100 billion in losses in each year from 2010-2012. These losses were disproportionately concentrated in geographic areas that were economically fragile before the crisis, and help to explain the lack of recovery in these areas.

Fully 44% of these losses, or close to $220 billion, occurred in ZIP codes above the 75th percentile of fraudulent income overstatement on mortgage applications.[20] Similar to the findings for the entire market, 70% of total losses can be accounted for by Liar's Loans. These prolonged losses are significant for the lack of recovery in these areas because existing research has shown that foreclosures have substantial negative externalities. Foreclosure sales cause house prices, and thus wealth, to decline for every home in the neighborhood, which depresses local aggregate demand. Mian, Sufi and Trebbi (2014) find that the causal effects of foreclosures can account for one-third of the total fall in house prices, one-fifth of the decline in residential investment, and one-fifth of the decline in auto sales. These effects contributed to the terrible performance of high income overstatement ZIP codes. Mian and Sufi (2015) found that these ZIP codes experienced negative income growth from 2005-2012, as well as increases

[20]The measure of income overstatement used in this paper is slightly different than that in Mian and Sufi (2015). The measure used in this paper matches census tracts to ZIP codes through the free program developed by the Missouri Data Center as in Adelino, Schoar and Severino (2015), rather than the proprietary bridging used in Mian and Sufi (2015).

in poverty and unemployment.

5 Robustness Analysis

Section 5 discusses the robustness of the main results presented in section 4. This section discusses the robustness of the results to different model specifications and the sensitivity of estimates to different levels of control group refinement, and formally tests for coefficient stability to bias from unobservable confounders using the analysis developed in Oster (2014). Overall, the main results hold up well across different specifications or levels of refinement, and are stable to bias due to unobservables.

The main results presented in section 4 are reasonably robust to model specifications with different geographic levels of fixed effects and different sample restrictions, and across loan types or purposes. The estimates are robust to including either state or county level fixed effects, which both produce slightly larger estimates than ZIP code level fixed effects. To an extent, ZIP code level fixed effects represent a conservative assumption, because it is known that fraud was clustered by ZIP code. Therefore the fixed effects may pick up some of the effect that is rightly attributed to the treatment indicator. These estimates are also consistent in the unrestricted full sample. Finally, the estimates are robust across loan types and purposes, with coefficients similar to those estimated in the full sample. In general, fixed rate loans, refinance, and cash-out refinance loans showed excess losses slightly larger than those previously estimated, while ARM mortgages and primary purchase loans showed excess losses that were slightly less.

The estimates are also reasonably robust to different levels of refinement. Unrefined and refined full documentation control groups produce estimates that range from \$93 - \$112 billion. This range brackets estimates produced by different levels of refinement. For example, the semi-refined group produces an estimate close to \$100 billion. Other alternative refinement restrictions also fall in this range. For example, I was concerned that refining the control group by removing loans from high fraud originators inadvertently removed too much data because only half of the observations had data for originator name, while all observations had servicer name data. To make sure that this was not the case, I coded the servicers for high fraud servicers and reintroduced the data that was dropped. The results for the semi-refined and fully refined group for this model were slightly larger than \$100 billion. Therefore, it is reasonable to conclude that the range of estimates given by the unrefined and refined control groups credibly bracket the sensitivity of the estimates to different levels of refinements.

While the visual comparison of the estimates produced by differing levels of controls in Table 3 suggest that the estimates are reasonably stable, it is still useful to formally test for coefficient stability using the method developed in Oster (2014). This analysis formally tests for the stability of coefficients to bias due to unobservable confounders by comparing co-movements in coefficients and

R^2 in models which include and exclude controls. The bias adjusted coefficients are defined as:

$\beta = \beta_{long} - (\beta_{short} - \beta_{long})\frac{(R^2_{max} - R^2_{long})}{R^2_{long} - R^2_{short}}$,

where β is the bias adjusted beta, β_{long} and R^2_{long} are the coefficient and R^2 from the regression which includes controls, β_{short} and R^2_{short} are the coefficient and R^2 from the regression without controls, and R^2_{max} is the maximum R^2. The short regressions correspond to the no control model specification in Table 3, while the long regressions correspond to the preferred specification. The test is performed under the assumption of equal selection, which assumes unobservables are equally as important as observables. Additionally, the test uses the recommended R^2_{max} of $1.3 * R^2_{long}$. As described in Oster (2014), this assumption for R^2_{max} is conservative because only 90% of true results estimated using constructed data survive this threshold.

Table 5: Results from Oster Bias Adjustment for Fully Refined Estimates

	Loss ($)	Loss/Original Balance	Foreclosure (%)	Delinquency (%)
Adjusted Coefficient	19124	.08615	.01908	.1003

This test shows that the estimates are stable and that any bias due to unobservables is likely slight. All bias adjusted coefficients are quite close to non-adjusted coefficients. The estimate of excess losses conditional on foreclosure is still close to $20,000. The adjusted foreclosure rate is still roughly 2 percentage points. Losses as a share of the original balance are within a half percentage point of the non-adjusted estimate. Finally, the delinquency rate is slightly higher than the non-adjusted estimate. Therefore this test suggests that any bias due to unobservables is slight even if we assume that unobservables are equally as important as observables.

The estimates produced in this paper are stable across specifications and robust to different modeling assumptions. However, it needs to be emphasized that these estimates are best interpreted as conservative lower bounds for the true causal effect of fraud on excess losses to foreclosure for three main reasons. First, the refinements may not have completely removed fraud from the control group because the estimates of excess delinquencies are still much lower than those estimated in research that directly observes fraud. Second, the COP selection bias is likely not entirely mitigated by the inclusion of controls for risk. This understatement is also concerning because the effects from loss conditional in foreclosure were substantially less than those due to extra foreclosures. Finally, the sample appears broadly representative of the market in terms of risk measures, and also contains a broad portion of the market. However, there is reason to believe that the practices at Wells Fargo may have been less fraudulent than average for the market. For these reasons, the estimates may understate the true effects of fraud. While these estimates of show that a substantial portion of the losses in this market are due to fraud, they are best interpreted as a conservative lower bound.

6 Conclusion

The findings in this paper and the broader research on fraud have shown deep seated problems with deception in the structure of financial intermediation. Accurate disclosure of the quality of collateral backing securities is a minimum condition for the basic functioning of asset markets. However, this condition was not met on a widespread basis, with disastrous consequences. These problems with deception led to historic losses of wealth for savers who invested their retirement funds in these bogus securities, for borrowers who were given mortgages that were counter to their best interests, and for the communities which experienced the prolonged foreclosure crisis. Losses in no/low documentation Liar's Loans account for 70% of total losses to foreclosure in the data. A conservative lower bound estimate for excess losses suggests that $100 billion, or roughly 30% of total Liar's Loans losses, can be considered excess. Moreover, 44% of total losses occurred in ZIP codes with the highest levels of fraudulent income overstatement on mortgage applications. These areas were particularly poorly suited to bear these losses, and the prolonged losses to foreclosure in these neighborhoods helps to explain the terrible economic performance of these areas throughout the Great Recession.

Borrowers and savers lacked sufficient protections against fraud in part because, at the time, the dominant view was that these protections were unneccesary. It was argued that in a free market financial institution's interest in maintaining their reputation would be sufficient to prevent dishonest activities on a large scale. Moreover, complex financial innovations were seen as efficiency enhancing because they allowed prices to more fully reflect new information about fundamentals. A sad irony of the financial crisis is that at precisely the time that these arguments were being made, all of the major financial institutions involved in the sale of mortgages were falsifying and misrepresenting the information needed to accurately price these innovations. Instead of reputation providing incentives for honest dealing, the reputation of the major financial institutions was used to support the deception by making investors less suspicious of the securities they purchased (Akerlof and Shiller, 2015).

In light of the widespread problems revealed by the financial crisis, the dominant pre-crisis view of the impossibility of dishonest practices should be seen as naive, and now discredited. To address these problems will require the creation of new protections for borrowers and savers, as well as more aggressive enforcement of existing protections. Moreover, financial regulation needs to prioritize increased monitoring of financial institutions, limit extreme executive compensation, and criminally prosecute financial institution senior executives engaged in deception and fraud.

References

Adelino, Manuel, Antoinette Schoar, and Felipe Severino. 2015. "Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle

Class." *National Bureau of Economic Research.*

Akerlof, George A. 1970. "The market for" lemons": Quality uncertainty and the market mechanism." *The quarterly journal of economics*, 488–500.

Akerlof, George A, and Paul M Romer. 1993. "Looting: the economic underworld of bankruptcy for profit." *Brookings papers on economic activity*, 1–73.

Akerlof, George A, and Robert J Shiller. 2015. *Phishing for Phools: The Economics of Manipulation and Deception.* Princeton University Press.

Angrist, Joshua D, and Jörn-Steffen Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton University Press.

Ben-David, Itzhak. 2011. "Financial constraints and inflated home prices during the real estate boom." *American Economic Journal: Applied Economics*, 55–87.

Black, William K. 2013. *The best way to rob a bank is to own one: How corporate executives and politicians looted the S&L industry.* University of Texas Press.

Commission, Financial Crisis Inquiry. 2011. "The Financial Crisis Inquiry Commission Report: Final Report of the National Commission on the Causes of the Financial and Economic Crisis in the United States."

Crotty, James R. 2009. "The Bonus Driven Rainmaker Financial Firm: How These Firms Enrich Top Employees, Destroy Shareholder Value and Create Systemic Financial Instability." University of Massachusetts Amherst, Department of Economics.

FBI. 2007. "Financial Institution Fraud and Failure Report Fiscal Years 2006 and 2007."

Galdston, Benjamin, Dave Kaplan, and Lucas Gilmore. 2014. "Who Can You Trust? The Failure of RMBS Trustees to Protect Investors." *The Advocate for Institutional Investors.*

Garmaise, Mark J. 2015. "Borrower misreporting and loan performance." *The Journal of Finance*, 70(1): 449–484.

Griffin, John M, and Gonzalo Maturana. 2014*a*. "Did Dubious Mortgage Origination Practices Distort House Prices?" *Available at SSRN 2485308.*

Griffin, John M, and Gonzalo Maturana. 2014*b*. "Who facilitated misreporting in securitized loans?" *Journal of Finance, forthcoming.*

Jiang, Wei, Ashlyn Aiko Nelson, and Edward Vytlacil. 2014. "Liar's loan? Effects of origination channel and information falsification on mortgage delinquency." *The Review of Economics and Statistics.*

Keys, Benjamin J, Tanmoy K Mukherjee, Amit Seru, and Vikrant Vig. 2010. "Did securitization lead to lax screening? Evidence from subprime loans." *Quarterly Journal of Economics.*

McCrary, Justin. 2008. "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test." *Journal of Econometrics.*

Mian, Atif, Amir Sufi, and Francesco Trebbi. 2014. "Foreclosures, House Prices, and the Real Economy."

Mian, Atif R., and Amir Sufi. 2015. "Fraudulent Income Overstatement on Mortgage Applications during the Credit Expansion of 2002 to 2005." National Bureau of Economic Research Working Paper 20947.

Oster, Emily. 2014. "Unobservable selection and coefficient stability: Theory and evidence." *NBER Working Paper.*

Piskorski, Tomasz, Amit Seru, and James Witkin. 2013. "Asset quality misrepresentation by financial intermediaries: Evidence from RMBS market." National Bureau of Economic Research.

SIFMA. 2015. "US Mortgage-Related Issuance and Outstanding."

Taub, Jennnifer. 2014. "Other People's Houses." *Yale University Press.*