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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 2007-2009. Existing research has shown that a substantial portion of the poor performance of the loans securitized in this market was caused by fraudulent origination practices, and that these practices were misrepresented to investors who purchased securities based on these loans. However, to date no paper has estimated the effects of mortgage fraud on losses from foreclosure in this market. This paper fills this gap by 1) Accounting for total losses from 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 they were higher than the expected losses for investors, had the loan quality information disclosed to them been accurate, instead of fraudulent. I find that Liar's Loans account for roughly 70% of total losses, and 36% of losses in Liar's Loans can be considered excess. Projected to the level of the entire market, this implies that $345 billion of the $500 billion in losses from foreclosure are accounted for by Liar's Loans. Roughly $125 billion, or 25% 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 to collateralize these securities was associated with fraudulent or negligent origination practices, 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 investors that purchased these securities by all major intermediaries involved in the sales of

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mortgages (Mian and Sufi, 2017; Griffin and Maturana, 2016b; Piskorski, Seru and Witkin, 2015; Garmaise, 2015; Jiang, Nelson and Vytlacil, 2014; Black, 2013; Keys et al., 2010; Ben-David, 2011).[2] However, as of writing no paper has yet estimated the effect of fraud on losses from foreclosure in the loans used as collateral for these securities.

This paper seeks to fill this gap by 1) Accounting for total losses from foreclosure due Liar's Loans from 2007-2012, and 2) Estimating what portion of total losses can be considered excess from the perspective of the investor. Losses on Liar's Loans are considered excess if they are greater than the expected losses that would have occurred if the loan quality information disclosed to investors was accurate, rather than misrepresented. The main findings in this paper suggest that losses from 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 on Liar's Loans account for roughly 70% of total losses in the data, and over one-third of Liar's Loans losses of can be considered excess. Scaled 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, $125 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 from foreclosure by comparing losses on loans in the no/low documentation treatment group, with losses on loans with identical 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 (Griffin and Maturana, 2016b; Jiang, Nelson and Vytlacil, 2014). To address this issue, qualitative information on high fraud originators from lawsuits regarding the actual loans in the dataset is used to refine the control group by removing loans originated by these institutions.[3] Regression discontinuity models based on those in the literature are then used to confirm the presence of fraud in the full documentation control group, and show that refinement eliminated fraudulent contamination.

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 from 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. Market regulations and contractual obligations that require the accurate disclosure of asset quality are a necessary condition for the basic

[2] The term fraud is used in this article in the economic sense and should not be seen as having any legal significance. See page 4 for a full definition.

[3] These lawsuits are discussed in section 3.3.

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, 2016b; Piskorski, Seru and Witkin, 2015). The basic issue underlying these lawsuits is succinctly 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."[4] [emphasis added]

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 executives involved in misrepresentation, increase investor recourse for violations of stated representations, and limit extreme compensation packages for executives to reduce incentives for looting (Black, 2013).

The findings are also relevant for historical narratives of the role of household balance sheets in the financial crisis because losses from foreclosure imply that household wealth had already been entirely wiped out. In addition to loss of wealth for the individual homeowner, losses from foreclosure have substantial negative externalities that cause 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, 2015). 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 loss of household wealth through decreasing retirement savings.

The prolonged losses from 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 from 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 from foreclosure from 2008-2012, or roughly $220 billion, occurred in ZIP codes with the highest levels of

[4] 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

fraudulent income overstatement on mortgage applications.[5] 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, 2017).

2 Literature Review

This section will review the basic description of fraud in the private mortgage securitization supply chain that emerges from the existing research, and describe how the main results in this paper contribute to this body of literature. Fraud is defined as deception or misrepresentation with the intent 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 there is no direct 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, 2016b). Therefore fraud is the most accurate term, even if not the most polite, 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 investment banks for distribution. The investment banks packaged 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 2007-2009. A substantial body of research has now documented a high incidence of mortgage fraud throughout both the origination and distribution portions of this supply chain. 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 Commission concluded that a systemic breakdown in accountability and ethics was an essential cause of the crisis (FCIC, 2011).

At originating institutions, there was a systematic abandonment of underwriting standards in order to increase the volume of loans originated, with no regards to quality. Mortgage fraud through the falsification of borrower financial information helped to increase origination volume through allowing institutions to originate larger loans than otherwise possible (Taub, 2014; Black, 2013; FCIC, 2011; Hudson, 2010). Empirical

[5] The measure of income overstatement used in this paper is similar to that in Mian and Sufi (2017), with one small difference. Similar to Mian and Sufi (2017) I use HMDA data to construct average borrower income recorded in mortgage applications at the census tract level, and IRS income data to construct average income at the ZIP code level. However, I match census tracts to ZIP codes through the free program developed by the Missouri Data Center as in Adelino, Schoar and Severino (2016), rather than the proprietary bridging used in Mian and Sufi (2017).

research has now systematically documented a high incidence of misrepresentation in securitized loans, which resulted in a higher chance of default (Griffin and Maturana, 2016b; Piskorski, Seru and Witkin, 2015; Garmaise, 2015; Ben-David, 2011; Keys et al., 2010; Jiang, Nelson and Vytlacil, 2014). For example, (Gri n and Maturana, 2016b) found that roughly 48% of securitized loans included misrepresentation along just three easy to measure dimensions, misreported owner occupancy status, unreported second liens, and appraisal value inflation, and that these loans were 51% more likely to default.

Liar's Loans were particularly useful in abetting this behavior because there was less documentation to falsify.[6] To be sure, no documentation loans were not prohibited, as long as the stated income and assets were accurate. However, as their colloquial name indicates, these loans were not used to accurately state borrower financial information. Indeed, loan officers often coached borrowers to falsely state their information, or falsified borrower documents without the borrower's knowledge.[7] As a result these loans performed particularly poorly, with a 5-8 percentage point higher default rate than full documentation loans (Jiang, Nelson and Vytlacil, 2014).[8]

The obvious question that emerges is how could abandoning underwriting standards ever have been in the interest of the originating institution? A common interpretation is that this was simply the result of risky bets gone wrong.[9] However, this interpretation is not wholly convincing because it cannot explain the large payouts received by executive officers of the originating institutions, even when their institutions failed.[10] Indeed, these risky bets paid off quite handsomely for the executive officers, even if they resulted in ruin for their institutions. In my reading of the literature, the most convincing interpretation that is able to explain the pattern of extreme executive compensation, despite the abandonment of underwriting standards resulting in the bankruptcy of their firms, comes from fraud expert Bill Black, who argues that executives looted their companies.

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,

[6] The break room at one Ameriquest/Argent branch was dubbed the Art Room, because it contained all the tools necessary to falsify documents. For example, sta members would cut out a name from a W2 income tax form with low income, and simply glue it on a W2 form with high income (Hudson, 2010). No documentation loans streamlined this process because they did not rely on falsifying W2's.

[7] For example, Omar Khan, a loan officer at subprime originator 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 FBI study, which found that 80% of fraud cases involved collusion or collaboration with industry insiders based on investigations and fraud reports (FBI, 2007).

[8] 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.

[9] For an example of this interpretation, see the post-mortem analysis of New Century Capital performed by Landier, Sraer and Thesmar (2010), with critical response in Black (2013).

[10] These payouts often took the form of bonus compensation that was not required to be paid back if the institution failed. Compensation estimates for executives at the largest 25 subprime originators has been compiled by the Center for Public Integrity, and is available at The https://www.publicintegrity.org/business/finance/whos-behind-financial-meltdown/subprime-25

resulting in bankruptcy. Looting has been described as bankruptcy for profit (Akerlof and Romer, 1993). Mortgage fraud helped executives loot their institutions because it increased short-term revenues that could be extracted. Fraud was particularly useful for increasing short-term revenues because in addition to allowing institutions to increase the volume of loans, fraudulent loans tended to have high initial fees attached to them as well as higher interest rates. Before losses occurred, these fees allowed originators to report high short-term revenue, and their balance sheets would also look strong due to the higher interest rates on their assets (Black, 2013).[11] 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 looting interpretation is also 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).

In the distribution portion of the supply chain, 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 (2015) 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.[12] All major sellers of private MBS have had numerous lawsuits initiated against them.[13] Forensic auditing has found that in some cases as high as 99% of the

[11] Black (2013) also argues that this pattern of behavior was very similar to the fraud which occurred during the S&L scandal of the 1980s.

[12] The typical offering documents included prospectus supplements which described the quality of collateral underlying 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 falsification, were still fraudulent because they violated the representations made in offering documents.

[13] An older list of 58 lawsuits filed from 2008-2012 can be found in the appendix to (Piskorski, Seru and Witkin, 2015). 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

loans in an issuance were in violation of underwriting practices stated in offering documents. Additionally, once defective loans were detected, RMBS Trustees failed to protect investor interests through curing defective loans or enforcing loan buy backs. 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).

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, where sellers have inside information concerning the quality of the products they sell, 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 due to lack of buyer access to inside information. 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; Piskorski, Seru and Witkin, 2015).

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.[14] Due to this hidden increase in leverage, the loan would also be expected to lose more in foreclosure. The findings in this paper contribute to the existing literature by providing the first estimate of total losses from foreclosure caused by Liar’s Loans, and estimating what portion of total losses can be considered excess. Additionally, this paper is the first to use data from the Columbia Collateral File, and so also confirms existing findings using novel data.

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

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.

[14] 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.

Recession. These estimates of losses from foreclosure provide a quantitative description of one of the mechanisms that caused this poor performance. For example, Mian and Sufi (2017) construct a measure of fraudulent income overstatement on mortgage applications at the ZIP code level.[15] They find that high income overstatement ZIP codes performed significantly worse with higher default rates, negative income growth, increased poverty, and increased unemployment. Additionally, Griffin and Maturana (2016a) 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 from 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 unnecessary 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, 2015).

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.

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. To my knowledge this study is the first to use this dataset in the context of empirical research on fraud. However, the sample is compiled from trustee reports so it is most similar to the data used in Griffin and Maturana (2016b) and Piskorski, Seru and Witkin (2015). The main advantages of this data relative to others used in the literature is that this data is publicly available and contains detailed information on losses from foreclosure. It is not clear if information on losses from foreclosure is available in the other data sources used in the empirical

[15] 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.

literature. However, in either case no other paper has directly measured the dollar value of losses from foreclosure due to fraud.

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 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 declined 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).

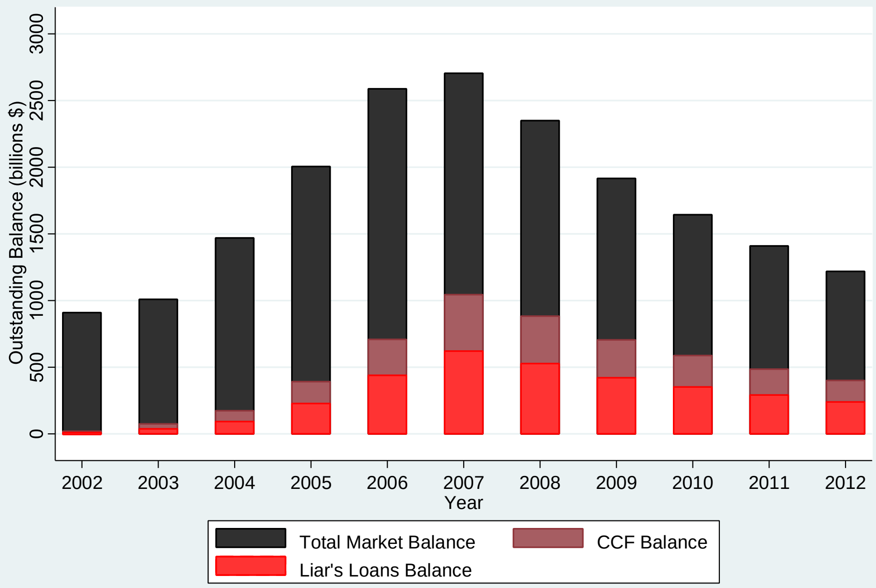
The CCF data from 2007-2012 appears to be broadly representative of the entire market. In general, the data accounts for a substantial portion of the entire market and mirrors the growth of the market. Also, the summary statistics of observable risk measures are similar to those in Griffin and Maturana (2016b) and Piskorski, Seru and Witkin (2015). The dataset also contains loans originated by roughly 2000 different institutions.[16]

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. This restriction is similar to that employed in Griffin and Maturana (2016b), to make my results comparable to those in the literature. The pooled sample is built by merging the December data to provide a retrospective

[16] 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.

Figure 1: Outstanding Balance of Private Label RMBS Market



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

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.

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 quantify 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 from foreclosure in no/low documentation loans, which can be identified through the variable document type. 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 section 3.3.

3.2 Identification Strategy and Regression Model

Fraudulent loans cause higher expected losses from foreclosure because fraud misrepresents borrower's financial information to give them larger loans than they would otherwise qualify for. My research design identifies the causal effects of fraud on excess losses from foreclosure by comparing losses for loans in the no/low documentation treatment group with losses for loans with identical risk measures in a refined full documentation control group. Higher expected losses in the treatment group which cannot be explained by observable risk measures are consistent with the causal effects of fraud.

The use of full documentation loans as a counter-factual for no/low documentation loans is particularly appropriate because reduced documentation loans were explicitly represented in offering documents as not being riskier than full documentation loans. Offering documents specifically stated that loans were only eligible for reduced documentation if underwriting standards determined them to be low risk.[17] Therefore, any additional risk by documentation type violates representations made to investors, and would be considered excess loss. The highly detailed loan-level data allows me to construct a rich counterfactual control group of full documentation loans which are identical along every observable risk measure available to investors. These measures include the FICO score, LTV ratio, loan type/purpose, amount of loan, and origination year. The ne-grained geographical detail of the data also allows me to use within ZIP code and default year variation between treatment and control groups to control for differences in local economic conditions or time-varying spatial heterogeneity. In addition, I conduct the Oster (2016) robustness test in section 5 to formally assess the stability of estimated coefficients due to selection on unobservables.

There is one main threat to identification that has been identified in the literature: the presence of fraud in the full documentation loan control group. Fraudulent contamination in the control group would cause the estimate of excess losses to understate the true effects of fraud (Jiang, Nelson and Vytlacil, 2014). The widespread incidence of fraud in full documentation loans in this market has also been independently confirmed by Griffin and Maturana (2016b) and Piskorski, Seru and Witkin (2015). For example, Griffin and Maturana (2016b) 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

[17] Offering documents stated that loans received a score based on different risk characteristics, and that this score which would be used to determine the stringency of underwriting. They stated that only loans deemed low risk might be eligible for a reduced documentation program, while medium to higher risk transactions would be subject to more stringent review. For example, offering documents included boiler plate language such as, "The Mortgage Score is used to determine the type of underwriting process and which level of underwriter will review the loan file. For transactions which are determined to be low-risk transactions, based upon the Mortgage Score and other parameters (including the mortgage loan production source), the lowest underwriting authority is generally required. For moderate and higher risk transactions, higher level underwriters and a full review of the mortgage file are generally required. Borrowers who have a satisfactory Mortgage Score (based upon the mortgage loan production source) are generally subject to streamlined credit review (which relies on the scoring process for various elements of the underwriting assessments). Such borrowers may also be eligible for a reduced documentation program and are generally permitted a greater latitude in the application of borrower debt-to-income ratios," (National Credit Union Administration Board v. Wells Fargo Bank, National Association, 2014).

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.

I use a simple linear regression model with a binary treatment indicator to estimate higher than expected losses in the treatment group. The regression model is:

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

where y_{izt} 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 separately.

The four outcome variables I measure are: 1) a binary variable coded 1 for foreclosed loans, 2) a binary variable coded 1 for delinquent loans, 3) losses from foreclosure in dollar values, and 4) losses from foreclosure as a share of the original balance. The measures of foreclosures are based on the variable losses on liquidated property, which 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, and will be considered foreclosures for the purposes of this paper.

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 mortgages. 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 o for the FICO High Achievers list.[18]

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.

3.3 Refinement to the Control Group

I re ne the full documentation control group by removing a set of loans with a higher probability of containing fraud, which are identified using qualitative information from lawsuit documents concerning the actual loans in the dataset. These lawsuits describe in depth the widespread fraudulent practices at several large mortgage originators, and

[18] 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.

I remove full documentation loans from these institutions from the control group. I then use regression discontinuity models based on those in the empirical literature to confirm that the loans removed exhibited indicators consistent with fraud, and show that removing these loans produces a refined control group that is not meaningfully contaminated by fraud.

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. In its role as a trustee, Wells Fargo has been sued numerous times for not protecting investors' interests after defective loans were detected, and I utilize qualitative information from two of these lawsuit 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]. 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.

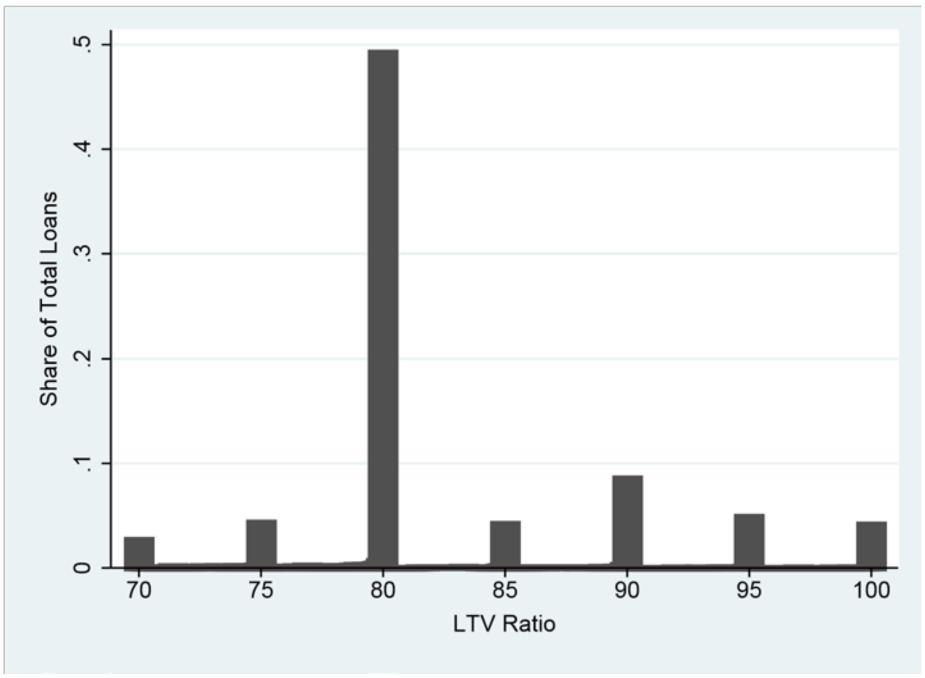
These lawsuits provide important qualitative information concerning the high incidence of fraudulent practices at particular loan originators, through sources such as interviews with loan officers and underwriters. Widespread fraud at a total of twenty-five institutions is discussed in depth in both lawsuits, and full documentation loans from these institutions are removed from my control group.[19] 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. The choice to remove high fraud loans is also supported by the analysis in Griffin and Maturana (2016b), which shows that the worst originators misreported at a significantly higher level than the best. Additionally, there is a large amount of overlap between the institutions identified in the lawsuit documents and those identified as high fraud originators in Griffin and Maturana (2016b).

I also validate my choice of refinement by conducting three tests using regression discontinuity models based on loans heaped at LTV intervals of 5. These models are based on the finding that a large portion of loans in this market were discontinuously heaped at LTV intervals of 5 units (75, 80, 85, etc.), which can be seen in Figure 2 below. Griffin and Maturana (2016b) find that appraisal overstatement was higher for heaped loans, and that loans with appraisal overstatement had a higher rate of default. They argue that a large portion of this pattern is more consistent with appraiser's targeting home valuations given by loan officers, rather than a random pattern of

[19] 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.

mistakes. The tests employed in this section 1) quantify the extent of heaping in the data, 2) estimate the difference in mean losses between heaped and non-heaped loans, 3) and conduct a sensitivity test using an external measure of fraud. As will be discussed in detail below, a summary of the findings from these tests is that the high fraud loans identified in lawsuit documents show substantial indicators of fraud, and thus are appropriate for removal. Moreover, removing these loans meaningfully reduces all indictors of fraud, and estimates based on the resulting refined control group are no longer sensitive to an external measure of fraud. On balance the results from these tests

Figure 2: Historgram of LTV Heaping at Intervals of 5



suggest that the refinement successfully purged any contamination from the control group that could threaten identification.

The first regression discontinuity model is the McCrary (2008) test, which helps to diagnose the presence of fraud by measuring the extent of heaping in the data. The test first divides the data into a rough histogram based on the LTV value, and then smooths the histogram on either side of the breakpoint being tested. Heaping is measured as the log difference in the height of the smoothed polynomials fitted on either side of the breakpoint. The heaping test only allows a single breakpoint to be tested, so the data are centered on the LTV intervals. The bin size of .1 is used because this is consistent with how the LTV values are recorded in my data, and I select the default bandwidth. Results for this test are presented in Table 1 and Figure 3 below.

The second test is based on the diagnostic suggested by Barreca, Lindo and Waddell (2016), for assessing whether heaped data would bias results from regression discontinuity model. This test uses regression to estimate whether the expected loss for heaped data is systematically different from non-heaped data, which would be consistent with fraud. I use this test to confirm that the high fraud loans identified in lawsuit documents are indeed contaminated, and that removing them from the control group meaningfully reduces the presence of fraud in the refined control group. To estimate differences in mean losses between heaped and non-heaped data, I use a regression discontinuity model similar to that in Griffin and Maturana (2016b). The regression discontinuity model includes an indicator for heaped loans, and controls for a fourth degree polynomial of LTV. The model is:

$$y_{izt} = \alpha_z + \gamma_t + \beta_0 + \beta_1 Z_0 + \beta_2 ltv^2 + \beta_3 ltv^3 + \beta_4 ltv^4 + \Lambda X_i + \varepsilon_i$$

where Z_0 is an indicator variable for loans at LTV heaps, and the rest of the controls are the same as those used in the main regressions. The excess loss measured by the estimated coefficient for Z_0 are distinct from the excess loss presented as the main result. The coefficient for Z_0 measures excess loss 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 are reported in Table 1.

Table 1 presents results for regression estimates of differences in mean loss between heaped and non-heaped data in columns 1 and 2, while column 3 presents results from the McCrary test. T-statistics are reported in parentheses for excess loss, while standard errors are reported in parentheses for the heaping test. The table compares results for the unrefined full documentation control group, full documentation loans from high fraud originators, and the refined full documentation control group which removes full documentation loans from high fraud originators. These groups are also compared for no/low documentation loans.

There are two basic findings in this table. First, the high fraud full documentation loans identified in lawsuit documents indeed show the highest amount of indicators associated with fraud, and removing these loans from the unrefined control group significantly reduces fraudulent contamination in the control group. For example, the McCrary tests in Table 1 show that high fraud full documentation loans exhibit more heaping than unrefined or refined full documentation groups. Indeed, the log difference in the height of polynomials fitted to either side of the breakpoint was 3.57, which is similar to the log difference of roughly 3.6 found for all no documentation loan groups. Additionally, removing these loans from the unrefined full documentation group reduces heaping from a log difference of 3.47 in the unrefined control group, to 3.29 for the refined full documentation group. This suggests that removing the high fraud loans from the unrefined control group was appropriate, and meaningfully reduces contamination. The pattern in the difference in heaping between high fraud, unrefined, and fully refined full documentation loans can also be seen below in Figure 3. Figure 3 shows that high fraud loans had the highest amount of heaping, while the refined control group had the least amount of heaping.

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

	Excess Negative Outcomes		Heaping
	Loss/Orig Balance	Loss ($)	Log Difference
Full Doc			
Unrefined	0.00612***	1560.2***	3.47
	(23.40)	(24.34)	(.004)
High Fraud	0.00756***	1830.6***	3.57
	(13.46)	(11.78)	(.008)
Refined	0.00400***	1238.8***	3.29
	(7.54)	(8.70)	(.008)
No Doc			
Unrefined	0.00900***	3065.9***	3.62
	(32.78)	(30.86)	(.004)
High Fraud	0.00916***	3530.1***	3.63
	(15.58)	(14.96)	(.008)
Refined	0.00804***	3065.9***	3.59
	(14.31)	(16.16)	(.007)

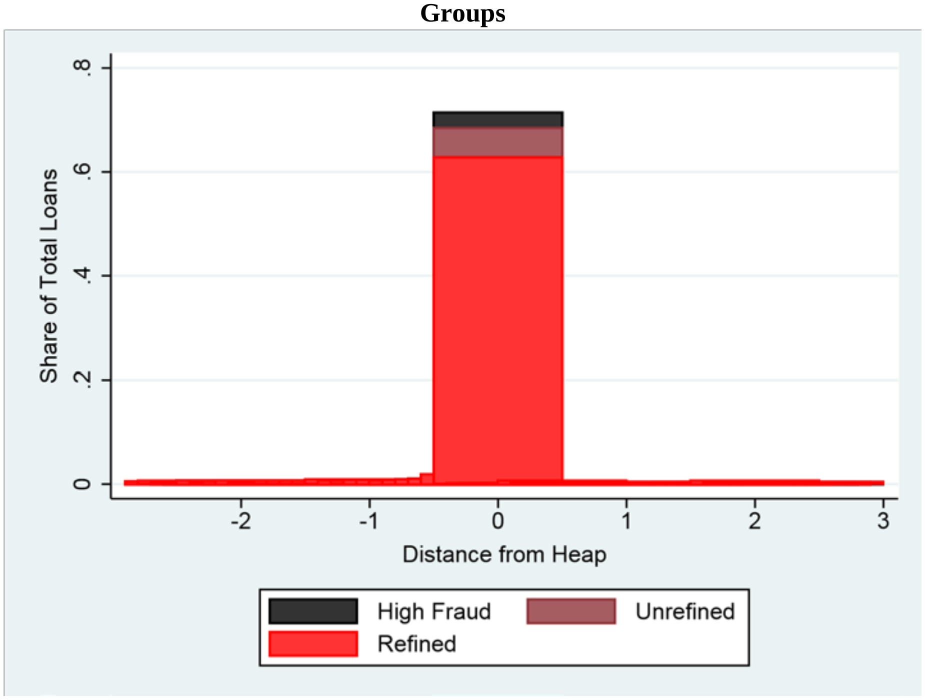
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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. 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 refined group removes all loans from high fraud originators.

The test for differences in mean loss for loans at heaps presented in Table 1 also confirms that high fraud full documentation loans are contaminated, and that removing these loans from the unrefined control group significantly reduces contamination. Expected loss for high fraud loans at heaps was $1,830 more than non-heaped high fraud loans, which was larger than the difference of $1,560 for the unrefined full documentation group. Consistent with the findings from the McCrary (2008) test, removing the high fraud loans reduces the difference in expected loss to $1,238.8 for the refined control group. Additionally, the t-statistic for the difference in expected loss in the refined control group was substantially smaller than those estimated for all other groups, suggesting that the difference in expected loss was far less consistent than those for the other groups. Overall, these results confirm that loans from high fraud originators contaminated the control group, and that removing them meaningfully reduces contamination.

The second primary finding in Table 1 is that measures consistent with fraud are found for all no/low documentation groups, including the refined group. The positive finding for the refined no documentation groups is significant because it suggests that it is unlikely that the reduction in fraud indicators for the refined full documentation control group is spurious. All no documentation groups show similar amounts of heaping. The difference in expected loss for heaped loans is also substantially similar for no documentation loans, with high fraud loans showing a slightly higher difference.

Figure 3: Net Heaping for High Fraud, Unrefined, and Refined Control Groups



While the above tests showed that removing high fraud loans from control group reduced all indictors associated with fraud, there are still some weak indicators which remain in refined group. There is still some positive heaping, although it is substantially less than for other groups. Additionally, there is still a small difference in expected loss between heaped and non-heaped data, although this difference was much less than those estimated for other groups, and much less systematic as indicated by the smaller t-statistic. To assess if these weak positive indicators would be sufficient to bias my results, I also employ a final sensitivity test in this section which uses an external measure of fraud, based on income overstatement at the ZIP code level. To perform this test, I split my sample into high and low ZIP codes based on the median level of income overstatement, and test whether the estimated difference in expected loss is sensitive to being conducted in high and low fraud ZIP codes. To the extent that the refinements successfully purged contamination from my control group, we would expect the difference in loss to be relatively insensitive to whether the model is run in high fraud or low fraud samples. To the extent that fraud remains in the control group, we would expect estimates to increase in the high fraud sample, and decrease in the low fraud sample.

Table 2 presents the results from estimating the difference in expected loss for heaped and non-heaped loans in high and low income overstatement ZIP codes, with a t-statistic for this difference in the final column. The primary finding in this table is that difference in estimates for the unrefined control group in high and low fraud samples is significantly different, while the difference in estimates for the fully refined group is not. The difference in expected loss for the unrefined group is $1,800 in the high fraud ZIP code, and $975 in the low fraud ZIP code. This difference is significant, with a t-statistic of 6.55.

Table 2: Excess Losses at LTV Heaps by ZIP Code Income Overstatement

	High Fraud	Low Fraud	t-stat
Unrefined	1799.8***	975.1***	6.55
	(87.02)	(91.03)	
Refined	1380.6***	937.6***	1.53
	(190.3)	(219.1)	

Standard errors in parentheses

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

In contrast, the estimates from the refined control group show much less variation between high and low fraud samples, with the difference in estimates not significantly different from zero. The estimates ranged from $937.6 in the low fraud sample, to $1,380 in the high fraud sample, but both had large standard errors of roughly $200. This implies that the t-statistic for the difference in estimates between high and low fraud samples for the refined group was only 1.53. Moreover, neither estimate is different by even a single standard error from the effect estimated in the full sample of ZIP codes. The lack of sensitivity of the results for the refined specification increases my confidence that the weak positive indicators detected for the refined control group in Table 1 are not large or systematic enough to bias my main results. Additionally, the positive finding for the unrefined group also suggests that the null finding for the refined group is not spurious.

Overall, the weight of evidence from the previous three tests confirms that the high fraud loans are appropriate for removal, and gives me reasonable confidence that the final refined control group is not meaningfully contaminated by fraud. The high fraud loan group showed the largest indicators of fraud from the tests based on McCrary (2008) and Barreca, Lindo and Waddell (2016). After these loans were removed, the tests for the final refined control group showed substantially smaller indicators than other groups, which were much less systematic. A final sensitivity test also showed that the indicators for the refined group were not systematically different when estimated in high and low fraud samples, while those for the unrefined group were. This pattern suggests that the weak indicators for the refined control which remained in Table 1 were not large or systematic enough to bias my main results.

To further confirm that my main results are not biased, I also perform a final sensitivity test in the robustness section. This diagnostic tests for whether the main results are significantly different when I remove heaped loans from the sample. Barreca, Lindo and Waddell (2016) show that removing heaped loans also removes the bias induced by them, so comparing results from specifications with and without heaped loans would reveal the size of any remaining negative bias. As will be discussed in further detail in the robustness section, removing heaped loans increases the estimated effects for the refined group by less than one-standard deviation. In contrast, removing heaped loans for the unrefined group significantly increases estimated effects. Based on the combined balance of evidence from the tests in this section and final robustness test, I have reasonable confidence that my refinement successfully removed any contamination that would bias my main results. However, it is worth noting for the skeptical reader that to the extent that I was unable to successfully purge contamination, then my estimates should be seen as a conservative lower bound for the true effects.

The final table in this section shows the distribution of covariates between the Liar's Loans treatment and refined full documentation control groups to check for balance on observables. Table 3 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. However, there are still over 650,000 loan-year observations in the control group, 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 7 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. In contrast, the control group lost slightly less of the original balance despite having a higher mean LTV.

Table 3: Sample Description

Panel A: Loan Information (Mean)		
	Treatment	Control
Original Balance ($)	324,749	277,596
Loan-to-Value	80.9	83.3
FICO Score	684.7	653.19
N	3,695,068	682,088

Panel B: Distribution of Risk Measures, Loan Type, and Purpose (%)		
	Treatment	Control
FICO Score		
Sub-Prime	12.5	35.2
Alt-A	20.4	21.3
Prime	55.2	32.6
High Achiever	11.9	10.9
Loan-to-Value		
LTV <= 80	80.3	62.5
80 < LTV <= 95	13.5	23.8
95 <= LTV	6.3	13.7
Loan Type		
Fixed Rate	32.7	46.8
Adjustable	67.3	53.3
Loan Purpose		
Purchase	53	39.11
Refinance	13.9	15.8
Cash-out Refinance	33.1	45.1

Loan Performance		
	Treatment	Control
Delinquency Rate (%)	46.8	40.4
Foreclosure Rate (%)	10.2	8.5
Mean Loss in Foreclosure ($)	176315	116304
Loss/Original Balance (%)	57.8	51.1
LTV if Foreclosed (mean)	81.6	84.4

4 Main Results

Section 4 presents the main results for total and excess losses from foreclosure caused by fraudulent Liar's Loans. A preview of the main findings in this section is that total and excess losses from foreclosure due to fraud were substantial, prolonged, and concentrated in neighborhoods particularly poorly suited to bear the losses. Losses from foreclosure for the entire private label RMBS market totaled $500 billion from 2007-2012. About 70%, or $345 billion, of these losses are accounted for by losses in no/low documentation Liar's Loans. Of this $345 billion, $125 billion can be considered excess. This implies that excess losses in Liar's Loans alone account for 25% of total market losses. Forty-four percent of total market losses occurred in ZIP codes above the 75th percentile of fraudulent 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 4 presents estimates of excess foreclosures, delinquencies, and loss. Table 5 scales these estimates to calculate total and excess losses for the entire market. Finally, Figure 4 shows the distribution of losses through time.

Table 4: Main Results: Excess Negative Outcomes for Liar's Loans in Pooled Sample

	No Controls	Some Controls	Preferred	Unrefined
Loss ($)	6546.5***	6660.0***	6602.5***	4290.2***
	(46.14)	(52.30)	(62.56)	(61.04)
Loss/Orig Balance	0.0168***	0.0179***	0.0187***	0.0120***
	(39.62)	(48.01)	(58.75)	(56.69)
Foreclosure Rate (%)	0.0176***	0.0214***	0.0233***	0.0175***
	(29.48)	(39.65)	(49.42)	(55.51)
Delinquency Rate (%)	0.0671***	0.108***	0.104***	0.0812***
	(42.68)	(80.50)	(88.20)	(103.13)
N	4377156	4377156	4377156	7018803

Table 4 shows the main results for excess foreclosures, delinquencies, and losses from 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 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 2.3 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. The excess loss in dollars for the preferred specification was $6,602.50. However, this average was produced with a foreclosure rate of only 10% in the treatment group, and so excess loss per foreclosure should be scaled appropriately to $66,025. Excess loss as a share of the original balance for the preferred specification were 1.87 percentage points of the original balance, but again should be scaled appropriately to 18.7 percentage points of the original balance per foreclosure. The average loss as a share of the original balance for the refined control group was 50%. This implies that Liar's Loans lost 35.4% more of the original balance per 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 loss from foreclosure was one-third smaller than those estimated for the refined specification. The difference in loss 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 refinement employed.

Excess delinquencies were also large and consistently averaged around 10 percentage points across specifications. This increase is quite substantial at roughly 25% greater than the average delinquency rate of 40.4% for the refined control group. The estimates of excess delinquencies are also within the range of estimates in the existing research. For example, the unrefined estimate of excess delinquencies was 8 percentage points, which is similar to the 5 - 8 percentage point increase for Liar's Loans reported by Jiang, Nelson and Vytlacil (2014) that was also based on an unrefined full documentation control group. Consistent with the expectation that the unrefined group was contaminated, the fully refined estimate is roughly 25 percent larger than the unrefined estimate. The delinquency estimate is also similar to those estimated by Piskorski, Seru and Witkin (2015) and Griffin and Maturana (2016b). That the results for delinquencies are within the range reported in the existing literature increases my confidence that the estimates for excess loss are also credible.

Table 5 shows the estimates of total and excess losses from 2007-2012 scaled to the level of the entire CCF dataset and entire market. The sample estimates are scaled to the level of the full CCF dataset using the share of Liar's Loans losses out of total losses in the CCF. The results are then scaled to level of the entire market using the CCF market share. The total number of foreclosures was substantial at 1.5 million in the

Table 5: Total and Excess Losses to Foreclosure for the Entire Private Label RMBS Market from 2007-2012 (billions $)

	Full CCF	Entire Market
Total Number of Foreclosures		
All Loans	1,473,244	4,091,345
Liar's Loans	890,960	2,474,284
Liar's Loans Excess	203,523	565,184
Total Foreclosed Balance		
All Loans	$321.54	$892.95
Liar's Loans	$220.05	$611.10
Total Losses to Foreclosure		
All Loans	$179.51	$498.51
Liar's Loans	$125.06	$347.30
Total Excess Losses		
Unrefined	$29.99	$83.11
Refined	$46.16	$127.91

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.[20] Therefore, the CCF dataset accounts for roughly 15% of total home forfeiture actions that occurred, and the private label market accounts for roughly 40%. Of the 4 million foreclosures generated by the privately securitized market, 2.5 million can be accounted for by Liar's Loans, and one-fifth of Liar's Loans foreclosures can be considered excess.

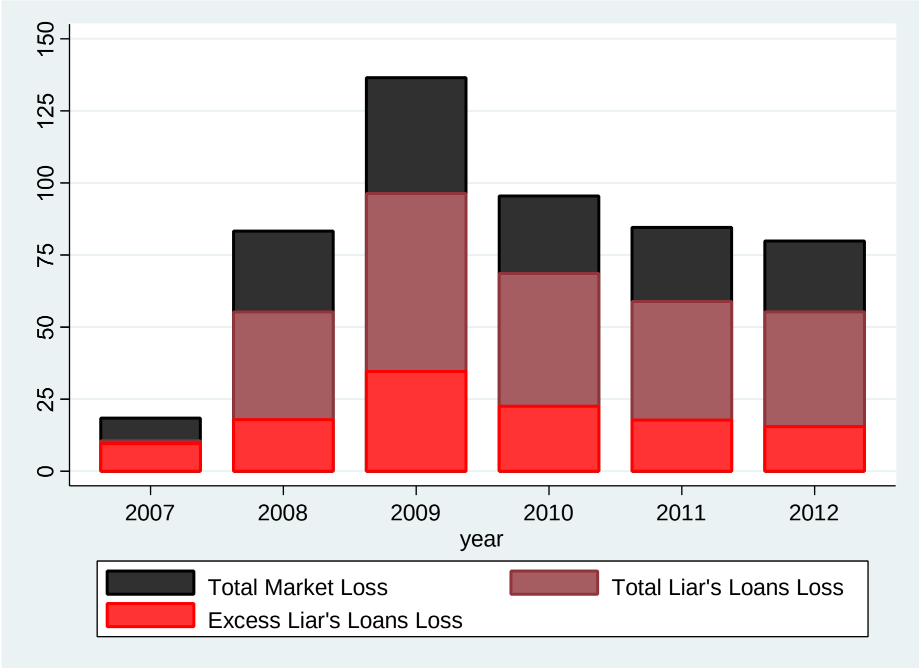
These foreclosures produced a high level of losses. The total foreclosed balance in the CCF was $321.5 billion, which implies a total market foreclosed balance of almost $900 billion. Over half of this foreclosed balance was not recovered through foreclosure auctions, with losses from foreclosure totaling $500 billion. Losses from Liar's Loans accounts for the lion's share of these losses at $345 billion, or roughly 70% of total losses. A substantial portion of Liar's Loans losses can be considered excess. At just over $125 billion, excess losses from Liar's Loans accounted for over

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

one-third of total Liar’s Loans losses, and one-quarter of total losses for all loans in the privately securitized market. A substantial portion of these excess losses were caused by the 565,000 excess foreclosures.

Figure 4 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

Figure 4: Total and Excess Losses Caused by Liar’s Loans from 2007-2012



because it shows that the bulk of losses from 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 from 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. Similar to the findings for the entire market, 70% of total losses in these ZIP codes 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 (2015) 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 (2017) found that these ZIP codes experienced negative income growth from 2005-2012, as well as increases 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, formally tests for coefficient stability to bias from unobservable confounders using the analysis developed in Oster (2016), and analyzes to what extent there may be any contamination left in the control group by comparing the main results to those produced without heaped loans. Overall, the main results hold up well across different specifications, are stable to bias due to unobservables, and do not appear to be affected by a contaminated control group.

The main results presented in section 4 are 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 when using the unrestricted full sample of all loans from the CCF. Finally, the estimates are robust across loan types and purposes, with coefficients similar to those estimated in the preferred sample. In general, fixed rate loans, refinance, and cash-out refinance loans showed excess loss slightly larger than those previously estimated, while ARM mortgages and primary purchase loans showed excess loss that was slightly less.

Table 6: Results from Oster Bias Adjustment for Fully Refined Estimates

	Loss ($)	Loss/Original Balance	Foreclosure (%)	Delinquency (%)
Adjusted Coefficient	6622	.0194	.0251	.1154

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 (2016). 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 (2016), this assumption for R^2_{max} is conservative because only 90% of true results estimated remain non-zero when using this threshold.

This test shows that the estimates are stable and that any bias due to unobservables is slight. All bias adjusted coefficients are quite close to non-adjusted coefficients, with many slightly larger than unadjusted coefficients. For example, the estimate of excess loss from foreclosure is slightly increased by \$20 to \$6,622, and the adjusted foreclosure rate is only two-tenths of one percentage point higher. Overall, this test suggests that even if we make the strong assumption that unobservables are equally as important as observables, any bias due to unobservables is slight.

Table 7: Main Results for Excess Negative Outcomes in Pooled Sample

	Original	Restricted	t-stat
Unrefined	4290.2***	5293.4***	8.53
	(70.28)	(94.34)	
Preferred	6602.5***	6732.9***	.74
	(105.5)	(141.5)	

Standard errors in parentheses

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

The final table in this section seeks to quantify any possible bias that remains from contamination in the control group. Barreca, Lindo and Waddell (2016) use constructed data to show that heaping induced bias in regression discontinuity models can be prevented by simply removing heaped data. I use this insight to conduct a final sensitivity test by comparing estimates of excess loss with and without heaped loans in the control group. To the extent that contamination in the control group was not successfully purged, we would expect estimates with heaped loans removed to be significantly larger than those without heaped loans removed. To the extent that fraud was successfully purged, we would not expect estimates with and without heaped loans to be significantly different.

Table 7 presents results from estimates with and without heaped loans removed from the full documentation control group, and a t-statistic for the difference in estimates. This test is conducted for both the unrefined and preferred specifications for better comparability. The basic pattern in this table is that removing heaped loans from the control group significantly increases the unrefined estimate, but does not significantly affect the preferred estimate, which is consistent with fraudulent contamination being successfully purged through refinement. Removing heaped loans from the unrefined control group produces a large increase in the estimate of almost

25%. This increase is highly significant as well, with a t-statistic of 8.5. In contrast, removing heaped loans from the refined control group only increases the estimate by $70. Scaled to the level of the entire market, this would only increase total excess loss from $128 billion to $130 billion. This increase is also less than a single standard deviation, and with a t-statistic of only .74, is not statistically distinguishable from zero. This suggests that if any contamination remained post-refinement, it would be too slight to systematically affect my results. Moreover, the large positive increases for the unrefined group suggest that the null finding for the refined group is not spurious. Overall, the balance of evidence from this sensitivity test, as well as the tests in section 3, gives me reasonable confidence that the refinement successfully purged fraud from the control group.

6 Conclusion

The findings in this paper and the broader research on fraud have shown deeply rooted 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. The problems with deception led to historic loss of wealth for savers who invested their retirement funds 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 from foreclosure in the data. The estimates in this paper suggest that $125 billion, or over one-third 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 from 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 unnecessary. It was argued that in a free market a 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 senior executives engaged in deception and fraud.

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