Home Equity Conversion Mortgages: The Secondary Market Investor Experience

Jaclene Begley
Fannie Mae

Hamilton Fout
Fannie Mae & Kansas State University

Michael LaCour-Little (contact author)
Fannie Mae & California State University-Fullerton
michael_lacourlittle@fanniemae.com
202-752-3318

Nuno Mota
Fannie Mae

Disclaimers and Acknowledgments

The views expressed are those of the authors and not necessarily those of Fannie Mae or the Federal Housing Finance Agency. The authors are indebted to Susan Woodward and Stephanie Moulton who provided detailed comments on earlier versions of the paper and to Walt Scott who assembled much of the original loan performance data. Any errors are ours alone.

Electronic copy available at: https://ssrn.com/abstract=3055881

Home Equity Conversion Mortgages: The Secondary Market Investor Experience

Abstract

We analyze Fannie Mae's experience with the Home Equity Conversion Mortgage product. From 1993-2010, Fannie Mae acquired 492,465 of these loans, representing 75% of the total market. During this period, prior to recent program changes, credit screening was not an element in the underwriting process. Using loan and borrower characteristics, we model the probability of adverse terminations; and given adverse termination, loss severity. We then show how the addition of credit information affects our models. Finally, we use credit data to provide a counterfactual assessment of the extent to which better screening might have affected portfolio performance. We find that imposing a minimum borrower credit score of 620 would have prevented 22.7% of loans with credit information from being originated and, simultaneously, would have reduced adverse terminations by 31% and subsequent losses by nearly $250 million, or 32%.

Key words: reverse mortgage, seniors, life-cycle consumption smoothing

JEL Codes: J14, G21, R21, D15

Electronic copy available at: https://ssrn.com/abstract=3055881

Introduction

Reverse mortgages are financial contracts intended to facilitate consumption smoothing by older households who are house-rich but cash-poor. The expected aging of the United States is well-documented, as are the high share of homeowners among older cohorts (U.S. Census Bureau 2014), and the desire of older adults to remain in their homes as they age (Redfoot, Sholen, and Brown 2007). Yet, recent spikes in reverse mortgage defaults and foreclosures increased concern about the product's viability for all stakeholders: including borrowers, lenders, insurers, and investors. The Home Equity Conversion Mortgage ("HECM") is the Federal Housing Administration's government-insured version of the product which has captured the substantial majority of this market segment[1] since its introduction as a pilot demonstration project in 1989. Over the period 1993-2010, Fannie Mae played the role of major investor in the product, acquiring a total of 492,465 HECMs, or more than 75% of the total HECM endorsements during this time, of which approximately 181,000 are still outstanding as of 2017.[2] Fannie Mae entered conservatorship in 2008, and discontinued new HECM acquisitions in 2010. In this paper we use Fannie Mae's rich data on loan performance and borrower characteristics, including credit data, to model reverse mortgage terminations and resolution outcomes from the unique perspective of the secondary market.

Reverse mortgages are highly complex products and modeling their cash flows is no simple task. Minor changes to modeling assumptions can produce large swings in portfolio performance prediction and,

[1] Currently, there are only a handful of proprietary lenders operating in the "jumbo" reverse space. Even during the 2006-2007 high-volume period, there were only 7,000 private reverse mortgage originations, or an estimated 5-10% of the total market at the time. Additionally, some state agencies provide specialized reverse mortgages. (Oliva 2016, CFPB 2012) Fannie Mae also offered a proprietary reverse mortgage product, the HomeKeeper, which it discontinued in 2008.

[2] If we exclude 2010 originations, when Fannie Mae's activity in the space was minimal, we observe that over 85% of 1993-2009 HUD HECM endorsements were acquired by Fannie Mae, see Figure 1 for more details.

therefore, in calculations of economic value. In its 2016 annual report to Congress, the Department of Housing and Urban Development ("HUD") recognized the volatility of the overall HECM portfolio, stating:

"In contrast [to the "forward" portfolio's capital ratio] HECM's capital ratio has fluctuated widely over the past five years with no apparent trend toward improvement. Actuarial study results show HECM's capital ratio at negative 3.58% in FY 2012 followed by two cycles of significant recovery and decline to end FY 2016 at negative 6.90%. A key challenge facing FHA is to stabilize HECM's financial performance. Recent changes to the HECM program show preliminary positive results" (HUD, 2016, page 33).

Our effort here is to report actual investor experience with the original HECM product, prior to program enhancements that took place with the passing of the Reverse Mortgage Stabilization Act in 2013 and additional requirements that were implemented in 2014 and 2015 (IFE 2016). Those programmatic changes affected principal limit factors (PLFs, the reverse analog to loan-to-value ratios at origination), both to reduce initial cash draws (except in hardship situations) and to account for non-borrowing spouses younger than 62, the minimum age standard for reverse products generally. In addition, HECMs originated after April 2015 required a financial assessment and a credit history analysis, with the potential for Life Expectancy Set Asides to cover future tax and insurance payments for riskier applicants.[3]

As the largest purchaser of HECMs for two decades, Fannie Mae played an important role providing liquidity to HECM lenders. Additionally, Fannie Mae's HECM portfolio went through multiple macroeconomic cycles, allowing for a meaningful look at HECM performance and loan outcomes over time. HECMs are inherently risky, due to their delayed payment resulting in accumulating loan balances over the loan life, and their crossover risk (the risk that the loan balance increases beyond the home value). However, a unique feature of the HECM product is that loans that reach 98% of the maximum

[3] For details of the financial assessment and credit history analysis, see HUD: HECM FINANCIAL ASSESSMENT AND PROPERTY CHARGE GUIDE EFFECTIVE AFTER JANUARY 13, 2014, available online at https://portal.hud.gov/hudportal/documents/huddoc?id=13-28mlatch.pdf

claim amount can be assigned to HUD. This, coupled with FHA-provided mortgage insurance, provides additional protection for credit risk holders. Despite these extra assurances, Fannie Mae suffered economic losses with the HECM product, with losses (not offset by revenues for loans that were paid off) for liquidated loans totaling $1.2 billion (see Table 1). In this paper, we document Fannie's experience and show how it would differ with more restrictive borrower requirements.

We offer the unique perspective of the reverse mortgage secondary market, and build on prior literature documenting HECM borrower behavior, particularly a recent paper by Moulton, Haurin, and Shi (2015) that explores determinants of HECM defaults and the benefits of new program changes on potential borrower outcomes. Our additional contribution comes from our detailed data on borrower default behavior, termination outcomes, and adverse termination resolutions; which we use to model predictions of termination, adverse outcomes, and losses for HECMs that Fannie Mae purchased through 2010. Prior research in this area has not had access to this breadth of detail, particularly with respect to termination and resolution outcomes. Moreover, we obtained credit information for a subset of HECM borrowers in our sample, and document how incorporating this information and imposing a credit score threshold for HECM borrowing would have changed Fannie Mae's loan purchasing experience over the past decade. Our findings provide important insights for all reverse mortgage market stakeholders, but are particularly relevant to potential secondary market investors.

The balance of the paper proceeds as follows. In the next section, we present a survey of the existing research on reverse mortgages generally, and HECMs in particular, identifying open questions that our work here may be able to address. In the third section, we describe the Fannie Mae data used, including descriptive statistics. In the fourth section, we present a set of models used to predict initial draw amounts (or share of principal limit taken out at origination), and subsequent loan performance (payoff, assignment, and adverse outcomes, including: asset liquidation via pre-foreclosure sales (PFS), third-party sale (TPS) or as real estate owned (REO)). The fifth section evaluates the extent to which a simple policy of not offering loans to borrowers with a credit score below 620, Fannie Mae's current standard eligibility requirement in the "forward" mortgage space, might have affected the experience with this product had such a policy been in place. The final section concludes and offers possible avenues for future research.

Literature Review

Home equity makes up a large portion of homeowner net worth, especially in recent years after the Great Recession and the financial crisis. Although the potential pool of reverse mortgage borrowers is quite large, only about 2% of eligible households actually have a reverse mortgage, and from 1989 to 2012 there were fewer than 1 million HECMs originated (CFPB 2012). The housing boom in the early-2000s saw an increase in reverse mortgage originations compared to the prior decade, particularly as prices were rising (Shan 2011). The total volume of HECMs originated nationally per year grew sharply from 2001 through 2008, but fell after that, returning to 2005 volumes in 2016 (Begley, Lambie-Hanson, and Witowski 2017). Despite this recent decline, reverse mortgage use is still projected to increase with the aging Baby Boomer generation; given the large share of housing in household total wealth and the overall desire of older adults to age in place (Carter and Miller 2017).

Many studies highlight general geographic and socioeconomic disparities in reverse mortgage usage. For example, Shan (2011) shows that HECMs are more likely to originate in neighborhoods with relatively high housing values but lower incomes, consistent with the product's appeal to households who are `house-rich but cash-poor.' HECM originations were also correlated with ZIP code-level housing price appreciation, particularly during the housing boom and in states with volatile housing prices histories

(Shan 2011; Haurin et al 2016). A number of studies find that reverse mortgages are more likely to originate in ZIP codes where households on average have lower credit scores and where there is a higher share of lower income and minority households (Bowen-Bishop, and Shan 2008; Shan 2011; Davidoff 2014; Begley and Lambie-Hanson 2015). Finally, there is evidence that reverse mortgage borrower socioeconomic characteristics are evolving over time.Redfoot, Scholen, and Brown (2007) show that the share of single female borrowers decreased in the early 2000s compared with the 1990s, while at the same time the average age of borrowers decreased, and average home values of borrowers increased.

The growing share of younger borrowers continued after the Great Recession, where there was an increase in borrowing among younger households with higher levels of debt, and defaults and insurance claims subsequently increased as well (Szymanoski, Lam, and Feather, 2017). This is attributed in part to the attractiveness of new HECM products offered in 2008 and 2010: fixed-rate lump-sum mortgages and the HECM Saver, which offered lower up-front costs. Fixed-rate mortgages outpaced adjustable-rate Lines of Credit (LOCs) after 2008, increasing from 12% to 69% of the market between 2009 and 2010. The fixed-rate lump-sum mortgages further increased HECM risk (Munnell and Sass 2014).

Increasingly adverse reverse mortgage outcomes led the FHA to request an appropriation in 2013 for the HECM Mutual Mortgage Insurance (MMI) Fund, and also led to federal programmatic changes with the Reverse Mortgage Stabilization Act of 2013 (Szymanoski, Lam, and Feather, 2017). As of 2014, 12% of reverse mortgages were in default due to taxes and insurance (T&I) (Integrated Financial Engineering 2014), and this is projected to increase in the coming years to 18% (Integrated Financial Engineering 2016). In a recent paper modeling T&I defaults, Moulton, Haurin, and Shi (2015) find that default risk increases for borrowers who have lower credit scores, withdraw larger amounts of equity in the first month of the reverse mortgage, who have higher property tax-to-income ratios, a history of late mortgage payments, or have a tax lien on their properties. They simulate how the new stricter loan qualifying requirements may influence reverse mortgage default rates, and find that imposing stricter standards—initial principal limits on withdrawals and T&I escrow account requirements— for credit scores below 580 would reduce default rates by about 50%. Another potentially important aspect exacerbating losses is introduced by Park (2017), who argues that disproportionately steep losses with reverse mortgage foreclosures when compared to “forward” mortgages foreclosures are due to overvaluation at mortgage origination, rather than property depreciation during the program.

There are a small number of papers exploring reverse mortgage borrower behavior, not specifically focused on T&I default. For example, Davidoff and Wetzel (2013) explore adverse selection into HECMs and show that very few borrowers draw credit from their HECMs later in the loan periodDavidoff (2015) provides additional evidence that borrowers are not behaving ruthlessly, failing to exercise a put option that would allow them to benefit from delaying credit line withdrawals until right before loan termination. Additionally, many studies find higher termination probabilities are correlated with socioeconomic characteristics—single male households, younger households, households with higher housing values, and those with lines of credit are all more likely to terminate their loans sooner than others (Bowen-Bishop and Shan 2008; Rodda, Lam, and Youn 2004; Shan 2011; Szymanoski, Enriquez, and DiVenti 2007). Davidoff and Welke (2007) also find that reverse mortgage holders tend to terminate their loans more quickly than similar populations would move out of their homes within the same state. This is particularly true for states with high levels of housing price appreciation, and they find the opposite is true in states with lower housing appreciation.

Beyond the borrower's experience, lenders and other holders of credit risk also face unique risks that create challenges for reverse mortgage products when compared to traditional "forward" mortgages. Early assessments of the nascent HECM program in the 1990s note three main risks faced in reverse mortgage insurance pricing: future interest rate risk, borrower longevity, and projected property values (Boehm and Ehrhart 1994; Szymanoski 1994). Similarly, the secondary mortgage market faces high costs of securitization due to unique challenges: the inflows and outflows of cash required (to the investor and to the borrower) inherent to the product; the timing of cash inflows only at loan termination; and crossover risk from negative amortization (Szymanoski, Enriquez, and DiVenti 2007; Szymanoski, Lam, and Feather 2017). Nevertheless, a robust secondary market is important for "facilitating growth for HECM loans through increased investment and expanded access to affordable financing for borrowers and lenders through additional capital inflows into securitized pools."(Szymanoski, Lam, and Feather 2017; p.56).

In light of this, Szymanoski, Enriquez, and DiVenti (2007) explore HECM termination risks from the perspective of the secondary market. They highlight the unique aspect of the assignment clause—a distinctive feature of the HECM program, and explore the influence of treating assignment as an additional form of reverse mortgage termination (along with mortality, moves, and other voluntary payoffs) when assessing termination-risk for the secondary market. They find that reverse mortgage borrowers are terminating their loans more quickly than general population mortality rates for their age-groups would predict, and this is particularly true of younger borrowers. Excluding assignments, the 10-year survival rate for all loans is 22%. Loan assignments start to influence loan termination hazard rates after year 6 for all borrowers in their analysis, and tend to occur more quickly as the borrower cohort age increases. Ultimately, including assignments in their termination model decreases the survival rates for all groups— reducing the 10-year survival rate for all borrowers to 14%. Despite increasing terminations, in later work, Szymanoski, Lam, and Feather (2017) note the importance of the assignment clause in providing added risk assurances to the secondary mortgage market.

While there are a handful of academic studies that focus on reverse mortgage terminations and defaults, none of them look at them from the unique perspective of the secondary market with information acquired by Fannie Mae. In particular, very few papers are able to include credit scores in their predictive models of termination or default, and none of the papers to-date provide a detailed empirical analysis of the different pathways to resolution once a default occurs.

Data

For our analysis, we rely on Fannie Mae internal data on monthly loan performance for HECMs that Fannie Mae purchased between 1993 and 2010.[4] Unlike the Ginnie Mae securitized product that currently dominates the secondary market, Fannie Mae kept HECM purchases on its balance sheet. For each loan we have detailed information on loan terms, loan performance, termination outcomes—including detailed resolution information for properties that enter default. Fannie Mae also acquired credit information for a subset (about 80%) of borrowers that originated loans between May 2005 and June 2009. We match credit scores to borrowers based on the credit report with the closest date to origination available. Although in some cases it is not an exact match, 95% of matches are within 5 months of the origination date (99% within 9 months). Figure 1 shows a comparison of the loan counts in our sample, including the subset with credit data, to HUD HECM endorsements. Note that, while HUD HECM endorsements are indexed by endorsement year, loans in the analysis sample are indexed by origination year, therefore the total in our sample exceeds HECM endorsements in certain years.

[4] This sample does not include the Fannie Mae HomeKeeper program, which only generated 7,172 mortgages and was discontinued in 2008. It also does not include a small share of mortgages originated prior to 1994.

Summary statistics for the Fannie Mae HECM purchases are included in Table 1, which breaks out the sample by loan status as of August 2017, the last date of observation for this paper. The top panel reflects the full dataset, and the bottom panels show the analogous information for the subsample for which we have credit score data. Of the full 492,465 loans purchased, 37% are active and the rest have terminated. Of the total active loans, 16% are classified as non-performing, which means that they are experiencing T&I or other delinquencies and are in the remediation or foreclosure process, or that the loan was recently called due but not yet terminated. For the remaining 311,030 loans, 45% were liquidated, meaning that they were either: (1) assigned to HUD because their principal balances rose to 98% of the maximum claim amount, (2) terminated through a pre-foreclosure sale, (3) went into foreclosure and then became Real Estate Owned (REO), or (4) experienced a third party sale (TPS) at foreclosure. Finally, the remaining 55% were terminated through non-adverse channels: paid-off, refinanced, or repurchased by the originator. For cases where the loan is not assigned to HUD, but there is an outstanding loan balance at termination, borrowers must sell the home to match either the lesser of 95% of the appraised value of the home or the unpaid balance of the loan. If there is still an unpaid loan balance after this process, lenders can access federal MMI insurance up to the maximum claim amount (MCA), which is the minimum of the appraised value or FHA’s loan limit at origination (IFE 2016, Perl 2017).

The bottom panels reflect some differences in mortgage outcomes across the subsamples with and without credit information. Due to their more recent origination timing, the loans with credit information are more likely to be active, and are slightly more likely to have non-performance issues or to have been liquidated through adverse channels (15% compared to 13%). Figure 2 shows the distribution of credit scores[5] for the sample, and reflects a wide range of credit scores, from 301 to 839. The majority of borrowers have scores above 700, with 43.7% above 740. There are also quite a few riskier borrowers, with 22.7% of the sample at 620 or below. This is consistent with the literature that notes the higher levels of borrowing in lower credit score neighborhoods.

Table 2 provides more information on the different termination outcomes for the non-active loans for the sample of loans with credit information. Of this sample, the majority of adversely terminated loans end in REO (10.4%, or 67% of the 75,955 liquidated). The second most likely outcome is assignment to HUD (2.5%), then TPS (1.5%), and followed by PFS (1.1%). The average unpaid principal balance once liquidated for these loans is $103,443. For the sample of non-adverse terminations, the majority of loans were paid off by the borrower (4.4%), or paid off but for an unknown reason (4.0%), death is the next most common cause of termination (2.4%), followed by loans repurchased by the originator (1.7%), refinancing (0.8%), and loans paid off because of a borrower move (0.5%).

Table 3 includes descriptive loan-level information for these data as of their last date of observation in the sample, again separated to reflect the information for the samples with and without credit scores. It also displays information on the five types of reverse mortgage structures that Fannie Mae purchased. These include: tenure, reflecting equal payments to the household as long as the loan is active; term, reflecting equal payments to the household for a set term only; modified tenure, where both scheduled payments and an LOC are available as long as the loan is active; modified term, where scheduled payments are available for a fixed term and the LOC is available as long as the loan is active; and LOCs.

[5] Our credit information is from Equifax. We use the Equifax Risk Scores, which are comparable to FICO scores and range from 300-850, for the main borrower on record.

Notably, we see a higher share of LOC borrowers in our credit sample, despite rules changing to favor fixed-rate mortgages during this time period.

While many variables are similar across the two groups, there are a few that are notably different, in part due to the newer vintages of the sample for which we have credit data (the average origination year for the credit sample is 2007, compared to 2003). For example, loans are more likely to be LOCs in the credit sample (89% to 81%), and to have drawn more against their principal limit at origination (66.6% to 58%). Again reflecting the later origination dates, the loans with credit experienced greater housing market volatility post-2005, the average housing price growth from origination to last observation is –23.57% for the sample with credit, compared with positive growth of 26.19% for the rest of the sample, measured using FHFA all-transactions 3-digit ZIP code housing price indices. The due and payable LTVs for the sample with credit are also much higher, with an average LTV of 84% for the credit sample compared to only 67% for the sample without credit. Unsurprisingly, losses, reflected in the average net loss variable, are also higher for the sample with credit. The net loss is measured as: unpaid balance + debenture interest + other expenses – net sales – HUD insurance payment – other receipts. Due to difficulties recovering accounting data for older loans , our net loss numbers are not net of all revenues received on all loans, but reflect only the losses on adversely terminated loans.

We observe some differences in borrower characteristics across our two samples as well. Primary borrower ages are similar, 81 for the sample without credit compared to 80, ages are top-coded at 95 in both samples. The borrowers with credit scores are also slightly less likely to be single and female, consistent with the earlier noted findings in the literature on the changing composition of borrowers during the early 2000s. The average primary borrower credit score is 703.

Models

We model Fannie Mae's loan experience along four separate dimensions capturing mortgagee borrowing and later loan performance. Our models follow consecutively as the outcome prognosis for each stage worsens, ending with predicting the loss severity experienced by the mortgage holder. First, we model the percentage of the principal limit that is drawn by the borrower at origination. We then explore mortgage terminations in more detail, first examining the likelihood of termination for our sample. This termination model is estimated on a dataset of annual snapshots of loans, through the end of 2016.[6] Next, given that a loan terminates, we model the probability of adverse termination, and then within adverse terminations, the probability of resolving in REO rather than PFS or TPS. Finally, we use the adverse termination sample to predict disparities in loss severity for these different adverse outcomes. We use different samples of our data for these four models, and Table 4 provides more information about these specific sub-samples.

Initial Draw Amounts

Borrower draws and HECM PLFs are important because they directly relate to potential crossover risk and the likelihood that a loan will be assigned to HUD for reaching the 98% MCA threshold. A number of studies highlight the positive relationship between loan balance and reverse mortgage risk (e.g., Moulton, Haurin, and Shi 2015, Munnell and Sass 2014, IFE 2016). We model initial draw behavior incorporating borrower and loan characteristics in a linear framework as follows:

$$Initial\ Draw\ Amount(i,t) = f(borrower\ age, borrower\ household, product\ type, \\ origination\ year\ FEs, state\ FEs) \qquad [1]$$

[6] Annual snapshots of the loan are used in the model, each 12 months apart, starting at 12 months after origination. Annual views end in 2016, the last full year of loan performance observed.

The dependent variable here is the initial draw percentage, which is the ratio of the initial loan balance to the principal limit at origination, where 100 reflects a loan balance equal to 100% of the principal limit. The covariates in this model include: a full set of dummy variables reflecting the borrower's age at origination; whether the borrower is a couple, single-female, or single-male household; the HECM product-type relative to an LOC; origination year fixed effects; and state fixed effects. Standard errors are clustered at the state-level. We exclude credit scores in our first model, but include credit scores at 50 point intervals in the second version of the model.

The results from this model are displayed in Table 5, with the first set of columns reflecting the results without credit scores, and then the second set of columns including credit scores. These results highlight the importance of HECM product-type, gender, couple-status of the household, and credit scores in influencing borrower loan draws at origination. For example, the first set of columns reflect that—within a given state, and year—single men draw a higher share of their loan at origination than single women or couple households. Households borrowing with term or tenure HECM products have drawn amounts relative to their principal limit at origination that are 29.72–38.44 percentage points lower than those using LOCs.

The addition of credit scores in the second set of columns shows similar coefficients on these variables, reflecting the consistent importance of HECM product type, gender, and couple-status on HECM draws, although the coefficients are slightly attenuated and are statistically different from the original model. The credit scores also provide some additional insight into borrower behavior. The relationship between credit scores and the percentage drawn at origination decreases monotonically as credit scores increase. Borrowers with credit scores of below 550 draw more of their loan relative to the principal limit at origination by 17.10–18.60 percentage points. Additionally, the R-squared of the model improves from .199 to .246 with the addition of credit information.

Termination

A termination is counted if and when the loan becomes due and payable (D&P) and/or is paid off/liquidated (whichever comes first). Loans that are assigned at 98% of MCA are included in the termination model; however, we observe that these loans do not terminate through to the assignment date, when they drop out of the estimation sample. Therefore, we do not observe when assigned loans terminate. In our data, reverse mortgages are terminated for several possible reasons: death of all borrowers; borrower(s) move out of the subject property; borrower refinances the loan; or (more rarely) the servicer declares the borrower in default due to non-payment of taxes and insurance or other reasons. Employing a maximum likelihood estimation method, the estimating equation for terminations is a logit model with the following form:

$$Prob\ (Terminate)_{i,t} = f(borrower\ age, current\ LTV\ thresholds, HPI\ change\ last\ 12\ mths\ HPI\ change\ since\ origination, borrower\ household, product\ type, seasoning, current\ year\ FEs, state\ FEs) \quad [2]$$

This is similar to the model used in the HUD HECM actuarial analysis, as shown in the IFE reports (2014-2016), although simpler, because we do not estimate separate models by termination-type. Other literature modeling reverse mortgage terminations employ similar strategies—many papers include controls for: borrower age, product-type, seasoning, couple-status, housing values and growth, and geographic location (for example, Bowen-Bishop and Shan 2008; Davidoff and Welke 2007; Rodda, Lam, and Youn 2004; Shan 2011; and Szymanoski, Enriquez, and DiVenti 2007).[7]

[7] Davidoff and Welke additionally highlight the importance of borrower health status in termination models; however, the majority of studies, including this one, do not have access to this information.

Using HUD's model as a guide, our simplified all-termination model includes all the variables included in the draw model above, although age and year fixed effects are now current age and current year fixed effects instead of the values at the time of origination. The model also accounts for seasoning, defined as years from origination date to the current date. In addition, the termination model includes the current LTV for the property, measured as loan balance over mark-to-market (MTM) value based on the 3-digit ZIP code-level HPI. We operationalize this variable with 20% intervals to account for nonlinearities in the relationship between current LTV and payoff. We also include the % change in the local HPI over the past 12 months, as well as the % change in the local HPI since reverse mortgage origination. Time is measured annually, in the origination month of the loan. Standard errors are clustered at the state-level. The results from this model are displayed in Table 6.

Similar to the results displayed in Table 5, with the first few columns reflecting the termination results without credit information, and the second set of columns showing the results with the credit information added. In general, our findings are consistent with the prior literature on terminations: we find that single male households have higher odds of terminating their mortgages, as do households who take out an LOC. The addition of the credit information does not change the odds ratios for the majority of the covariates; however, they provide some additional information on termination probabilities. As credit scores increase, the odds of terminating decrease.

Payoff versus Adverse Liquidation

Next we model the probability that, given a termination event, the borrower (or their heirs) pays off the loan in full. Our estimating sample, reflected in Table 4, is comprised of all terminations, including those that were adversely terminated. Adverse terminations occur when the borrower cannot cover the outstanding debt balance owed, and the servicer must initiate a resolution process. The specific results of the adverse termination process are explored in the next section. For this model predicting payoff, we again use a maximum likelihood estimation framework with a logistic distribution. The estimating equation for the payoff model is:

$$Prob(Payoff|Termination)_i = f(borrower\ age, D\&P\ LTV\ thresholds, HPI\ change\ last\ 12\ mths, HPI\ change\ since\ origination, borrower\ household, product\ type, T\&I\ distress\ flag, seasoning, D\&P\ year\ FE, state\ FEs\ ) \quad [3]$$

This model is similar to the termination model with a few additions. We use borrower age at liquidation rather than current age, and include a T&I distress flag to indicate whether the property ever experienced T&I delinquency. A borrower's ability to pay off the loan depends on the true home value at the D&P date relative to the size of their loan, which is likely to be less than our estimated MTM LTV based on the origination appraisal and local HPI changes. This is because the reverse borrowers may be less likely to perform maintenance on their property; particularly if their loans are underwater with no remaining net equity. We factor these effects in by using the current LTV as well as the loan seasoning, recent HPI changes, and D&P year FEs in the model, which proxy for current market conditions.

The results for this model are included in Table 7: the first few columns displaying the results without credit information in the model, and the second set of columns reflects the results with the inclusion of credit. In this model, credit information significantly changes the influence of some of the covariates. For example, the odds of payoff with a T&I distress flag are now slightly higher than before (.36 compared with .48), and the odds of payoff with the tenure product relative to LOC are lower, although still quite high (4.45). Consistent with theory, households with higher credit scores are more likely to pay off their loans, and this pattern is clear and significant: borrowers with credit scores less than 620 have are only

36% to 41% as likely to pay off the loan compared to those with a credit score over 740. We explore how the absence of these loans would affect overall outcomes and losses in the final section. In next two models, we further explore the pathways for loans that went through an adverse termination to explore whether credit influences termination outcomes once the balance exceeds the value of the underlying collateral.

REO

We next explore the type of adverse termination. For mortgages where the balance exceeds the value of the property there are a few paths to resolution, as detailed earlier. In the vast majority of cases, when borrowers (or their heirs) cannot pay off their reverse loan via a home sale or otherwise, and do not respond to pre-foreclosure sale (PFS) or deed in lieu (DIL) offers, then the properties go through foreclosure proceedings. In the foreclosure process, the home is typically either sold to a third party (TPS), or, if no buyer exists, converted to REO. At this point, the REO-holder can file an FHA insurance claim for the lesser of the appraised value of the home or the loan limit at origination, which means that there is still potential for losses on these mortgages when the appraised value does not cover the balance of the loan. The distinction between resolution type is nontrivial: as shown in Table 2, the net loss varies greatly between type, with average REO losses of $16,158 (11% severity), compared with $10,274 (5% severity) for TPS, and $1,872 (1% severity) for PFS.

To predict resolution type for the sample of loans that experience adverse terminations (borrower is unable to pay off when loan is D&P), we employ another logit model to assess the likelihood that this will result in an REO instead of a PFS or TPS at time of foreclosure:

$$
\begin{gathered}
Prob(REO|Adverse\ Liquidation)_i = \\
= f(borrower\ age, D\&P\ LTV\ thresholds, HPI\ change\ last\ 12\ mths, \\
HPI\ change\ since\ origination, borrower\ household, product\ type, T\&I\ distress\ flag, \\
seasoning, D\&P\ year\ FE, state\ FEs\ )
\end{gathered}
\qquad [4]
$$

This is the same model as the payoff model, but the sample is now restricted to loans experiencing an adverse termination, and the dependent variable is whether the property went into REO. The results from this model are shown in Table 8, and once again reflect the model results with and without credit information. In general, many of our variables are not significant in these models; for example, borrower household characteristics do not matter. The addition of credit information also does not change the odd ratios significantly across models. Notably, the credit variables themselves are not statistically significant, with the exception of the two lowest categories of 450 or lower and 450 to 500, which have larger odd ratios of REO of 1.17 and 1.14, respectively. LTV thresholds are consistently significant and increasing in LTV, with LTVs of greater than 1.2 having an odds ratios of 2.66.

Severity

Finally, we model the loss severity for loans that were adversely terminated and ultimately resolved, focusing on disparities across resolution-type. Loss severity is measured as a percentage of liquidation unpaid balance in our model. This represents the share of the loan that Fannie Mae was unable to recover after the resolution process was complete. This final sample includes all loans that were not paid off completely at termination: PFS, TPS, and REO resolutions, and we model loss severity linearly:

$$\begin{gathered} Loss\ Severity(i) = f(borrower\ age, D\&P\ LTV\ thresholds, HPI\ change\ last\ 12\ mths, \\ HPI\ change\ since\ origination, borrower\ household, product\ type, T\&I\ distress\ flag, \\ seasoning, D\&P\ year\ FE, state\ FEs\ ) \end{gathered} \quad [5]$$

This model includes additional flags for whether the property went into PFS, TPS, REO, and we additionally model interactions between credit scores and these three resolutions, to look at differences in loss severity across credit score by type of resolution. Results for this model are displayed in Table 9, reflecting three separate versions of the model. The first few columns show the coefficients without the addition of credit information, and highlight the increase in loss severity when properties enter REO. In a given year and state, relative to REO, PFS and TPS both experience lower levels of loss. Loss is also slightly lower when borrowers are couples or single females relative to single men. The MTM LTV thresholds are counterintuitive, but are again most likely not representative of true property D&P LTVs. Idiosyncratic property-specific issues affect the ultimate property sales value and are not captured by our MTM LTV measures at the neighborhood-level. Park (2017), for example, highlights issues with appraised valuations of reverse mortgage properties and explores their relationship with steep loss outcomes.

The second set of columns display the same information with the credit information, and none of the coefficients are statistically different from the initial model, with the exception of the T&I distress flag, which is insignificant in both models. As with the probability of REO model, credit information has a more subdued impact on model prediction ability relative to earlier models. Nonetheless, we still observe that borrowers with a credit score of 620 or lower have slightly higher severities, with estimated impacts ranging from 0.48 to 0.76 percentage points.

The third set of columns display interactions between the liquidation type and borrower credit score, to see if credit has an additional influence on loss severity by termination-type. For REOs, we see that the pattern of borrowers with credit scores of 620 or lower having higher severities is still present and more robust than seen in the second column estimates. We find no consistent strong pattern with respect to credit scores for TPS. For PFS terminations we see that lower credits scores are actually associated with smaller losses. One potential explanation for this pattern is that areas with larger shares of lower credit score borrowers, correlated with lower incomes, are more likely to be in the midst of a gentrifying process. Therefore investors seeking to purchase homes pre-foreclosure proceedings would be willing to pay more for properties in such areas, where the potential return on their investment would be higher, and therefore losses on these PFS sales are smaller.

While it may seem like the value of adding credit information diminishes with the stage of resolution once an adverse termination begins, credit significantly affects the probability of entering the adverse termination process. If credit thresholds were employed during loan originations, many of the loans would not reach the adverse stage. In the next section we examine this relationship further.

Effect of Imposing a Minimum Credit Score of 620

The results in the above section highlight the critical insights credit scores provide in predicting reverse mortgage outcomes. In recent years, as HECM outcomes worsened, requirements for HECM borrowers became more stringent. Today, while there are still no minimum credit score requirements for HECM borrowers, lenders are required to "evaluate the HECM borrower's willingness and capacity to meet his or her financial obligations and to comply with the terms of the mortgage."[8] In this section, we quantify how Fannie Mae's experience would have changed with credit restrictions for HECM borrowers at origination. We do this to assess how knowledge of borrower credit histories from the start would change the overall adverse outcomes and severity experience for investors.

We assess how Fannie Mae's experience would have changed if we restricted our sample to borrowers with a minimum credit score of 620, which is the current Fannie Mae standard eligibility requirement for "forward" borrowing. Table 10 shows the results from this exercise. The top panel reflects that the total losses Fannie Mae experienced as a result of adverse terminations, for the sample with credit

[8] https://hudgov.prod.parature.com/link/portal/57345/57355/Article/4907/What-is-the-minimum-credit-score-necessary-to-be-eligible-for-a-HECM

information this sums to $768 million. If we restrict the sample to loans with a minimum score of 620, these losses are reduced to $522 million. This reflects a 32.1% reduction in losses. Applying this same proportional effect to the overall sample, *i.e.* including loans without credit information, we see that the overall $1,195 million in losses would have been reduced by $383 million. Note that this estimate assumes the credit score distribution of loans without credit information would be the same as that for the sample with credit information.

This restriction also means that an estimated 41,197 fewer loans, or 22.7%, would have been originated, indicating that fewer borrowers would have been able to tap into their home equity via this product. Looking at the differences in volume across adverse termination type makes it clear that the majority of these savings would come from a reduction in REO outcomes, with an estimated 24,572 fewer properties going to REO, or 30.8%. This is similar to the analysis undertaken by Moulton, Haurin, and Shi (2015), who use a credit threshold of 580 and find a 29.8% reduction in HECM defaults and a 12% reduction in HECM originations. They also remove households with bad credit "indicators" with similar results.[9]

Conclusion

In this paper we use a unique dataset on HECMs purchased by Fannie Mae through 2010 to explore the influence of credit information and other borrower and loan characteristics on HECM outcomes. We build on prior literature by offering detailed data on adverse termination by type of resolution and loss severity. We also explore how different HECM outcomes change with the incorporation of borrower

[9] We also explore imposing a minimum score threshold of 580, or excluding borrowers with a bankruptcy in their credit history. Results are comparable but smaller in effect, leading to a 21.8% and 10.6% reduction in losses under the minimum score of 580 or no bankruptcy history policies, respectively.

credit scores. Finally, we show how the addition of credit information would change the outcomes and losses experienced by Fannie Mae.

Ultimately, we see that including credit provides essential information on borrower behavior and loan resolution in our models. Credit scores are important predictors of initial draw amounts, termination, and mortgage payoff. However, they are not as strong predictors of resolution outcomes or loss severity once a property has already reached these adverse termination stages.

While we don't see a strong influence of credit in predicting resolution type or loss severity given an adverse termination already initiated, we do see a strong improvement in the performance of loans and the severity of losses when we impose credit restrictions on our initial sample. Imposing a minimum borrower credit score of 620 at HECM origination would have reduced adverse terminations by 31%. Having borrower credit information at loan origination has the potential to result in better outcomes across the board for borrowers, lenders, insurers and investors. Incorporating this information could ultimately lower the costs of lending for all parties and help more older adults benefit from reverse products in the coming years.   Not addressed in this paper are more recent secondary market innovations, such as the GNMA security backed by HECMs.   Research on that topic is warranted.

References

Begley, Jaclene and Lauren Lambie-Hanson. 2015. "The Home Maintenance and Improvement Behaviors of Older Adults in Boston." *Housing Policy Debate,* 25(4): 754-781.

Begley, Jaclene, Lauren Lambie-Hanson, and Michael Witowski. 2017. "Reverse Mortgage Originations and Performance in Philadelphia." *Federal Reserve Bank of Philadelphia CFI Policy Note*.

Boehm, Thomas P. and Michael C. Ehrhardt. 1994. "Reverse mortgages and interest rate risk." *Real Estate Economics* 22(2): 387-408.

Bowen Bishop, Tanya and Hui Shan. 2008. "Reverse Mortgages: A Closer Look at HECM Loans." *NBER Working Paper.* http://www.nber.org/programs/ag/rrc/08-Q2%20Bishop,%20Shan%20FINAL.pdf

Carter III, George R., and Joshua J. Miller. 2017. "The HECM Program in a Snapshot." *Cityscape* 19(1): 119-126.

Case, B. and Schnare, A.B., 1994. Preliminary evaluation of the HECM reverse mortgage program. *Real Estate Economics*, *22*(2), pp.301-346.

Consumer Financial Protection Bureau (CFPB). 2012. *Report to Congress on Reverse Mortgages*. Washington, DC, June

Davidoff, Thomas. 2010. "Home Equity Commitment and Long-Term Care Insurance Demand." *Journal of Public Economics*, 94:44-49.

Davidoff, Thomas. 2014. "Reverse Mortgage Demographics and Collateral Performance." SSRN Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2399942

Davidoff, Thomas. 2015. "Reverse Demographics and Collateral Performance." *Homer Hoyt Institute Meetings*, January 2015.

Davidoff, Thomas, Patrick Gerhard, and Thomas Post. 2017. "Reverse mortgages: What homeowners (don't) know and how it matters." *Journal of Economic Behavior & Organization* 133: 151-171.

Davidoff, Thomas and Gerd Welke. 2004. "Selection and Moral Hazard in Reverse Mortgage Market." *SSRN*, October 21. Available at SSRN: https://ssrn.com/abstract=608666

Davidoff, Thomas and Gerd Welke, 2017. "The Role of Appreciation and Borrower Characteristics in Reverse Mortgage Terminations" *Journal of Real Estate Research*, 39(1):99-126.

Davidoff, T. and Wetzel, J., 2014. Do Reverse Mortgage Borrowers Use Credit Ruthlessly? *Working Paper, Sauder School of Business, University of British Columbia.*

Haurin, Donald, Chao Ma, Stephanie Moulton, Maximilian Schmeiser, Jason Seligman, and Wei Shi. 2016. "Spatial variation in reverse mortgages usage: House price dynamics and consumer selection." *The Journal of Real Estate Finance and Economics* 53(3): 392-417.

Integrated Financial Engineering Inc. (IFE). 2016. "Actuarial Review of the Federal Housing Administration Mutual Mortgage Insurance Fund, HECM Loans, For Fiscal Year 2016." Washington, DC: Federal Housing Administration.

Integrated Financial Engineering Inc. (IFE). 2015. "Actuarial Review of the Federal Housing Administration Mutual Mortgage Insurance Fund, HECM Loans, For Fiscal Year 2015." Washington, DC: Federal Housing Administration.

Integrated Financial Engineering Inc. (IFE). 2014. "Actuarial Review of the Federal Housing Administration Mutual Mortgage Insurance Fund, HECM Loans, For Fiscal Year 2014." Washington, DC: Federal Housing Administration.

Moulton, Stephanie, Donald Haurin, and Wei Shi. 2015. "An analysis of default risk in the Home Equity Conversion Mortgage (HECM) program." *Journal of Urban Economics*, 90: 17-34.

Munnell, A.H. and Sass, S.A., 2014. The Government's Redesigned Reverse Mortgage Program. *Center for Retirement Research at Boston College*, (14-1).

Oliva, Jason. 2016. "The State of the Jumbo Reverse Mortgage Market in 2016" *Reverse Mortgage Daily. https://reversemortgagedaily.com/2016/11/03/the-state-of-the-jumbo-reverse-mortgage-market-2016/*

Office of the Inspector General, U.S. Department of Housing and Urban Development (OIG HUD). 2014. *Audit of Home Equity Conversion Mortgage Program*, Audit Report # 2014-PH-0001, September 30.

Park, Kevin A. 2017. "Reverse Mortgage Collateral: Undermaintenance or Overappraisal?." *Cityscape* 19(1): 7-28.

Perl, Libby. 2017. "HUD's Reverse Mortgage Insurance Program: Home Equity Conversion Mortgages." Congressional Research Service #7-5700.

Redfoot, Donald, Ken Scholen, and S. Kathi Brown. 2007. "Reverse Mortgages: Niche Product or Mainstream Solution?" AARP Public Policy Institute Paper #2007-22.

Rodda, D.T., Lam, K. and Youn, A., 2004. Stochastic Modeling of Federal Housing Administration Home Equity Conversion Mortgages with Low-Cost Refinancing. *Real Estate Economics*, *32*(4), pp.589-617.

Shan, Hui. 2011. "Reversing the Trend: The Recent Expansion of the Reverse Mortgage Market" *Real Estate Economics,* 30(4): 743-768.

Szymanoski, Edward J. Jr. 1994. "Risk and the Home Equity Conversion Mortgage." *Real Estate Economics* 22(2): 347-366.

Szymanoski, Edward J., James C. Enriquez, and Theresa R. DiVenti. 2007. "Home equity conversion mortgage terminations: Information to enhance the developing secondary market." *Cityscape*: 5-45.

Szymanoski, Edward J., Alven Lam, and Christopher Feather. 2017. "Financial Sustainability and the Home Equity Conversion Mortgage: Advancing Fiscal Soundness and Affordable Financing for Senior Homeowners." *Cityscape: A Journal of Policy Development and Research* 19(1): 47-72.

U.S. Census Bureau (2014). “An Aging Nation” Available: https://www.census.gov/library/visualizations/2017/comm/cb17-ff08_older_americans.html

U.S. Department of Housing and Urban Development (HUD). 2015. “The Financial Status of the FHA Mutual Mortgage Insurance Fund, Fiscal Year 2015” *Federal Housing Administration, Annual Report to Congress.* Washington, DC, November 16

U.S. Department of Housing and Urban Development (HUD). 2016. “The Financial Status of the FHA Mutual Mortgage Insurance Fund, Fiscal Year 2016” *Federal Housing Administration, Annual Report to Congress.* Washington, DC, November 15

Figure 1 - Comparison of Analysis Sample and Total HUD HECM Endorsements

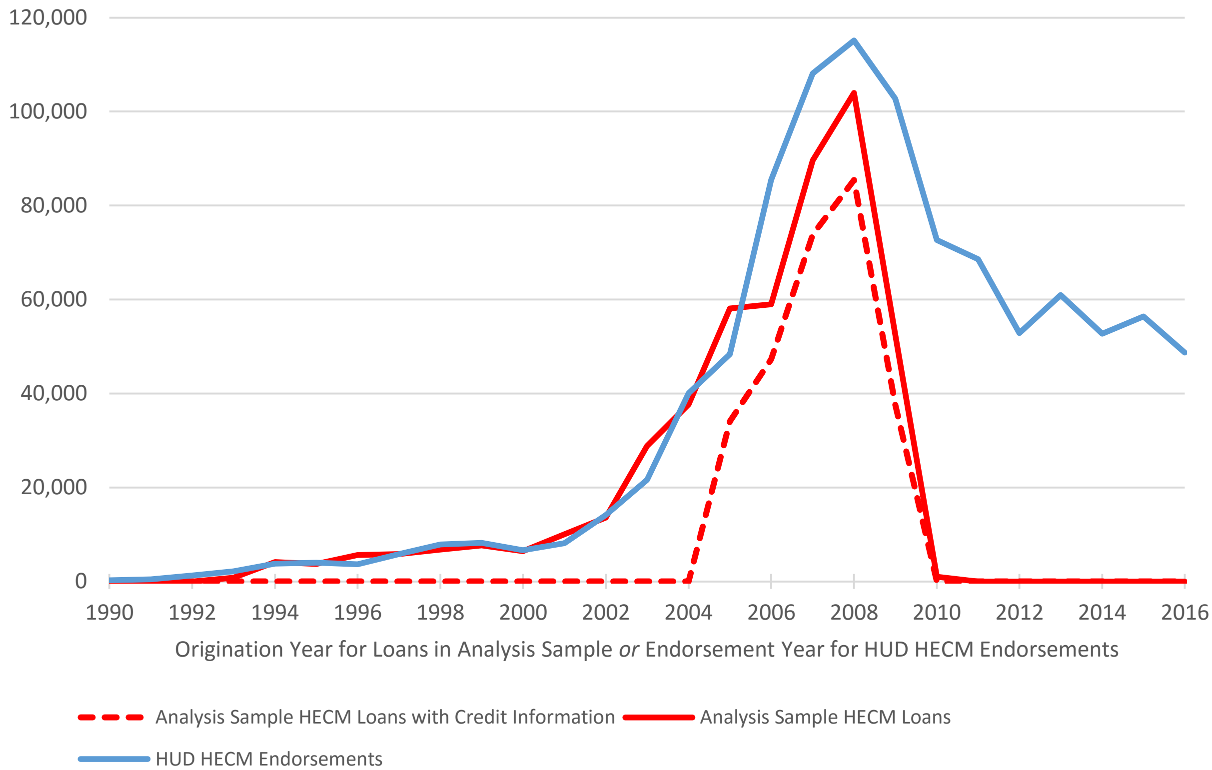

Figure 2 - Credit Score Distribution of Loans in Sample

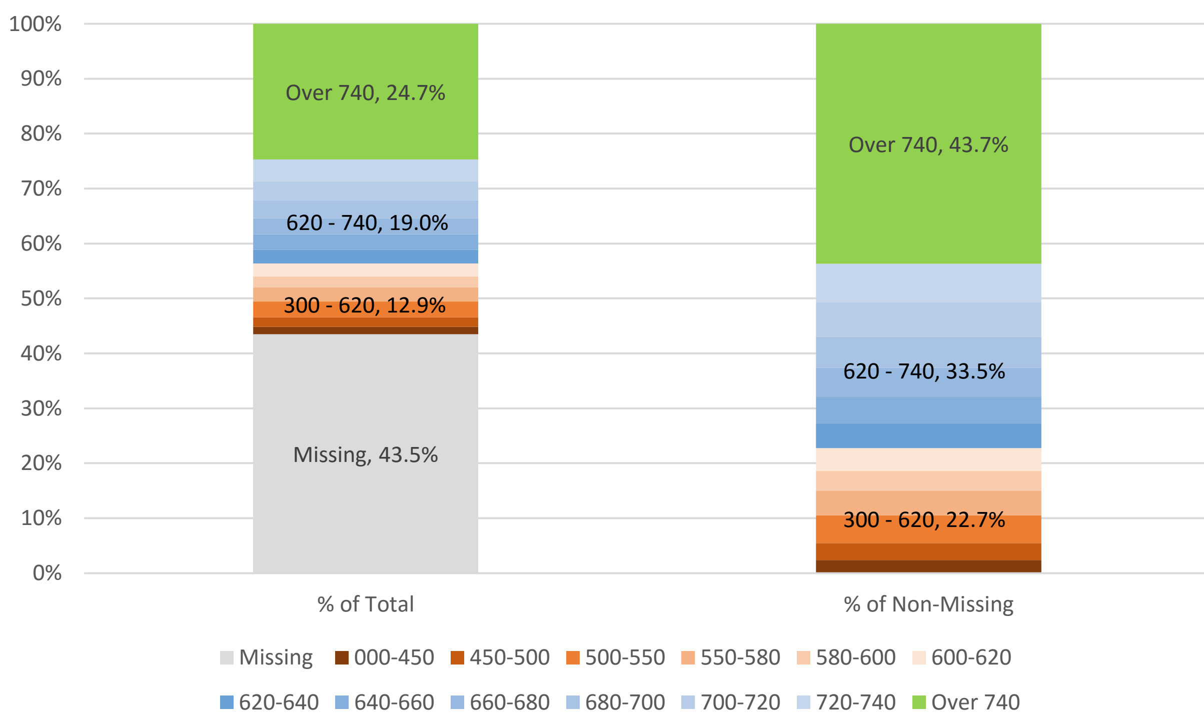

Table 1 Loan Status Summary Statistics

This table shows the volume and termination status of Fannie Mae HECM purchases from 1990 through 2010. The top panel displays the information for the entire sample, and the bottom panel breaks out the sample based on credit score availability. The information reflects the last loan observation for each loan in the data.

Panel A: Full sample

Product	STATUS	Origination UPB		Net Loss	Origination UPB	Current or Liquidation UPB *	Severity (% Liqd. UPB)	Net Loss	Origination UPB		Current or Liquidation UPB *	Net Loss
		N	% of N	N	Mean	Mean	Mean	Mean	Sum ($Mn)	% of $	Sum ($Mn)	Sum ($Mn)
HECM	Active and Performing	152,271	31%	0	$99,195	$187,016	.	.	$15,104	34%	$28,477	.
HECM	Active and Non-Performing	29,164	6%	0	$108,741	$201,578	.	.	$3,171	7%	$5,879	.
HECM	Liquidated	139,069	28%	121,174	$89,738	$169,765	6%	$9,858	$12,480	28%	$23,609	$1,195
HECM	Paid off, Refinanced, Repurchased	171,961	35%	0	$76,921	$132,914	.	.	$13,227	30%	$22,856	.
HECM	**TOTAL**	**492,465**	**100%**	**121,174**	**$89,312**	**$164,115**	**6%**	**$9,858**	**$43,983**	**100%**	**$80,821**	**$1,195**

Panel B: Comparison of samples with and without credit Information

Sample	STATUS	Origination UPB		Net Loss	Origination UPB	Current or Liquidation UPB *	Severity (% Liqd. UPB)	Net Loss	Origination UPB		Current or Liquidation UPB *	Net Loss
		N	% of N	N	Mean	Mean	Mean	Mean	Sum ($Mn)	% of $	Sum ($Mn)	Sum ($Mn)
W Credit	Active and Performing	113,943	23%	0	$103,505	$186,934	.	.	$11,794	27%	$21,300	.
W Credit	Active and Non-Performing	20,979	4%	0	$111,253	$195,710	.	.	$2,334	5%	$4,106	.
W Credit	Liquidated	75,955	15%	65,195	$103,443	$178,719	8%	$11,777	$7,857	18%	$13,575	$768
W Credit	Paid off, Refinanced, Repurchased	67,388	14%	0	$100,133	$159,465	.	.	$6,748	15%	$10,746	.
W Credit	**TOTAL**	**278,265**	**57%**	**65,195**	**$103,256**	**$178,700**	**8%**	**$11,777**	**$28,732**	**65%**	**$49,727**	**$768**
No Credit	Active and Performing	38,328	8%	0	$86,380	$187,261	.	.	$3,311	8%	$7,177	.
No Credit	Active and Non-Performing	8,185	2%	0	$102,303	$216,617	.	.	$837	2%	$1,773	.
No Credit	Liquidated	63,114	13%	55,979	$73,243	$158,989	6%	$7,624	$4,623	11%	$10,034	$427
No Credit	Paid off, Refinanced, Repurchased	104,573	21%	0	$61,963	$115,805	.	.	$6,480	15%	$12,110	.
No Credit	**TOTAL**	**214,200**	**43%**	**55,979**	**$71,197**	**$145,165**	**6%**	**$7,624**	**$15,250**	**35%**	**$31,094**	**$1,195**

* Current UPB mean and sum displayed for Active loans; Liquidation UPB for liquidated, paid off, refinanced, and repurchased loans.

Table 2: Current Status of Non-Active Loans with Credit Information

This table reflects information on the final resolution status for loans that were originated between May 2005 and June 2009 and terminated as of August 2017.

Category	STATUS	Origination UPB		Net Loss	Origination UPB	Liquidation UPB	Severity (% Liqd. UPB)	Net Loss	Origination UPB		Liquidation UPB	Net Loss
		N	% of N	N	Mean	Mean	Mean	Mean	Sum ($Mn)	% of $	Sum ($Mn)	Sum ($Mn)
Liquidated	Assignment to HUD	12,210	2.5%	12,087	$120,268	$226,025	0%	$1,048	$1,468	3%	$2,760	$13
Liquidated	PFS	5,433	1.1%	4,869	$121,657	$210,798	1%	$1,872	$661	2%	$1,145	$9
Liquidated	REO	51,019	10.4%	42,556	$95,690	$162,026	11%	$16,158	$4,882	11%	$8,266	$688
Liquidated	TPS	7,293	1.5%	5,683	$115,945	$192,395	5%	$10,274	$846	2%	$1,403	$58
Liquidated	**TOTAL**	**75,955**	**15%**	**65,195**	**$103,443**	**$178,719**	**8%**	**$11,777**	**$7,857**	**18%**	**$13,575**	**$768**
Paid off, Refinanced, Repurchased	Payoff: Death	11,575	2.4%	0	$88,511	$163,365	.	.	$1,025	2%	$1,891	.
Paid off, Refinanced, Repurchased	Payoff: Borrower Moved	2,296	0.5%	0	$80,541	$148,645	.	.	$185	0%	$341	.
Paid off, Refinanced, Repurchased	Payoff: By Borrower	21,555	4.4%	0	$104,419	$161,554	.	.	$2,251	5%	$3,482	.
Paid off, Refinanced, Repurchased	Payoff: Other/Unknown	19,707	4.0%	0	$101,262	$162,102	.	.	$1,996	5%	$3,195	.
Paid off, Refinanced, Repurchased	Repurchased	8,423	1.7%	0	$97,981	$141,296	.	.	$825	2%	$1,190	.
Paid off, Refinanced, Repurchased	Refinanced	3,832	0.8%	0	$121,795	$168,786	.	.	$467	1%	$647	.
Paid off, Refinanced, Repurchased	**TOTAL**	**67,388**	**14%**	**0**	**$100,133**	**$159,465**	**0%**	**$0**	**$6,748**	**15%**	**$10,746**	**$0**

Table 3: Summary Statistics for Loans with and without Credit Information

This table displays summary statitics for variables in the various models by samples based on availability of credit information

Panel A: Loans in Initial Draw, Payoff, REO vs PFS or TPS, and Severity Models

	Loans with Credit Information			Loans without Credit Information		
Variable	Mean	Std. Error	N	Mean	Std. Error	N
Active	0.485	0.0009	278,265	0.217	0.0009	214,200
Assigned	0.044	0.0004	278,265	0.140	0.0008	214,200
Payoff	0.242	0.0008	278,265	0.488	0.0011	214,200
REO	0.183	0.0007	278,265	0.125	0.0007	214,200
PFS	0.020	0.0003	278,265	0.011	0.0002	214,200
TPS	0.026	0.0003	278,265	0.018	0.0003	214,200
Initial Drawn Amount	66.61	0.058	265,902	58.01	0.079	163,559
Severity	7.60	0.051	65,194	5.16	0.050	55,978
Multiple Borrowers	0.360	0.0009	278,265	0.363	0.0010	214,200
Single Female	0.419	0.0009	278,265	0.471	0.0011	214,200
Single Male	0.222	0.0008	278,265	0.166	0.0008	214,200
Credit Score	696.5	0.195	278,265	.	.	0
Term	0.009	0.0002	278,265	0.019	0.0003	214,200
Tenure	0.017	0.0002	278,265	0.027	0.0003	214,200
Modified Term	0.047	0.0004	278,265	0.078	0.0006	214,200
Modified Tenure	0.037	0.0004	278,265	0.065	0.0005	214,200
Line of Credit	0.889	0.0006	278,265	0.811	0.0008	214,200
Origination Year	2007.2	0.002	278,265	2003.5	0.008	214,200
Due and Payable Year	2012.6	0.007	168,322	2008.8	0.012	177,309
Age at Origination	73.03	0.014	278,265	74.54	0.016	214,200
Borrower Age*	80.18	0.013	278,265	81.14	0.015	214,200
Seasoning	7.17	0.006	278,265	6.64	0.008	214,200
LTV at Due and Payable	84.25	0.094	167,045	67.36	0.093	158,243
DP LTV <= 60%	0.227	0.0007	278,265	0.466	0.0010	214,200
60% <DP LTV<= 80%	0.259	0.0007	278,265	0.224	0.0008	214,200
80% <DP LTV<=100%	0.254	0.0007	278,265	0.164	0.0007	214,200
100% <DP LTV<=120%	0.132	0.0005	278,265	0.077	0.0005	214,200
DP LTV > 120%	0.128	0.0005	278,265	0.068	0.0005	214,200
T&I Distress Issues	0.218	0.0008	278,265	0.139	0.0007	214,200
Orig. to DP HPI, 3-digit ZIP	-23.57	0.115	166,610	26.19	0.136	172,209
Last 12 mths HPI, 3-digit ZIP	0.946	0.012	278,265	3.340	0.018	214,200

Panel B: Loans in Termination Model						
Terminated	0.073	0.0002	1,695,893	0.104	0.0003	1,095,452
Current LTV	81.48	0.028	1,695,893	65.27	0.034	1,095,452
Cur. LTV <= 60%	0.239	0.0003	1,695,893	0.473	0.0005	1,095,452
60% <Cur. LTV<= 80%	0.296	0.0004	1,695,893	0.250	0.0004	1,095,452
80% <Cur. LTV<=100%	0.244	0.0003	1,695,893	0.153	0.0003	1,095,452
100% <Cur. LTV<=120%	0.109	0.0002	1,695,893	0.062	0.0002	1,095,452
Cur. LTV > 120%	0.113	0.0002	1,695,893	0.062	0.0002	1,095,452
Last 12 mths HPI, 3-digit ZIP	-0.88	0.008	1,695,893	1.05	0.010	1,095,452
Orig. to Cur. HPI, 3-digit ZIP	-15.38	0.015	1,695,893	0.31	0.026	1,095,452
Seasoning	4.61	0.002	1,695,893	5.25	0.003	1,095,452
Current Year	2011.7	0.002	1,695,893	2009.4	0.004	1,095,452
Credit Score	698.6	0.078	1,695,893	.	.	0
Current Age	76.59	0.005	1,695,893	77.868	0.006	1,095,452

* Borrower age is age at due and payable for loans that have terminated and current age for loans that are active.

Table 4: Model samples for loans with credit information

This table displays descriptive information for each of the specific model samples.

Status	Total with Credit Information	In Estimation Sample for Model: Initial Draw	Termination*	Payoff	REO vs TPS	Severity
Active and Performing	113,943	109,593	956,517			
Active and Non-Performing	20,979	20,226	162,387			
Liquidated	75,955	72,036	369,129	63,719	63,717	48,364
- Assignment to HUD **	12,210	11,345	86,466			
- PFS	5,433	5,188	27,949	5,426	5,426	3,581
- REO	51,019	48,534	223,325	51,001	50,999	39,182
- TPS	7,293	6,969	31,389	7,292	7,292	5,601
Paid off, Refinanced, Repurchased	67,388	55,960	207,860	58,708		
- Paid off	55,133	52,181	195,029	54,906		
- Repurchased	8,423					
- Refinanced	3,832	3,779	12,831	3,802		
Total	278,265	257,815	1,695,893	122,427	63,717	48,364

* Termination model is a loan by year sample.

** Loans that were assigned are observed in termination model even though they do not terminate while we still see them in our data.

Source: Author calculations from Fannie Mae HECM purchase data. Credit data is available for approximately 80% of loans originated between May 2005 and June 2009.

Table 5 - Initital Draw Amount Model

Dependent Variable is Initial Draw Percentage Measured as Loan Balance as a Percentage of Principal Limit at Origination (100=100% of PL) Standard Errors Clustered at the State Level						
		Base Model			Credit Model	
	Coef.	Std. Error	Prob>t	Coef.	Std. Error	Prob>t
Intercept	73.55	0.61	<.0001	67.66	0.40	<.0001
Multiple Borrowers	-4.49	0.25	<.0001	-2.81	0.23	<.0001
Single Female	-2.62	0.19	<.0001	-2.85	0.17	<.0001
Product-type: term	-29.72	1.98	<.0001	-26.56	1.64	<.0001
Product-type: tenure	-37.98	1.33	<.0001	-33.79	1.19	<.0001
Product-type: modified term	-33.82	1.37	<.0001	-31.43	1.17	<.0001
Product-type: modified tenure	-38.44	1.14	<.0001	-35.17	0.95	<.0001
Product-type: Line of Credit	0	.	.	0	.	.
450 or Lower				18.60	0.69	<.0001
450-500				17.50	0.59	<.0001
500-550				17.10	0.68	<.0001
550-580				15.60	0.60	<.0001
580-600				15.36	0.57	<.0001
600-620				14.65	0.46	<.0001
620-640				13.75	0.52	<.0001
640-660				13.19	0.49	<.0001
660-680				12.08	0.43	<.0001
680-700				10.46	0.34	<.0001
700-720				8.99	0.29	<.0001
720-740				7.12	0.20	<.0001
Over 740				0	.	.
State FE		51			51	
Age at Origination FE		34 (Ages 62-95)			34 (Ages 62-95)	
Origination Year FE		05 (Yrs 2005-2009)			05 (Yrs 2005-2009)	
R Squared		0.199			0.246	
N		257,815			257,815	
Sample Mean of Dep. Var.				66.49		

Excluded categories are: Single-Male, Line of Credit, Origination year 2009, State CA, Borrower Age at Origination 75, and Credit Score Over 740

Table 6 - Termination Model

Dependent Variable is Indicator of Loan Terminating Standard Errors Clustered at the State Level								
	Base Model				Credit Model			
	Coef.	Std. Err.	Od. Ratio	Prb>ChiSq	Coef.	Std. Err.	Od. Ratio	Prb>ChiSq
Intercept	-2.472	0.057		<.0001	-2.539	0.062		<.0001
1.00 <Cur. LTV<= 60	0	.	1	.	0	.	1	.
2.60 <Cur. LTV<= 80	-0.207	0.027	0.81	<.0001	-0.244	0.025	0.78	<.0001
3.80 <Cur. LTV<=100	-0.085	0.059	0.92	0.1511	-0.144	0.056	0.87	0.0094
4.100<Cur. LTV<=120	0.048	0.080	1.05	0.5527	-0.030	0.074	0.97	0.6852
5.Cur. LTV > 120	0.222	0.095	1.25	0.0199	0.127	0.088	1.14	0.1477
Last 12 months HPI, 3-digit ZIP	0.003	0.001	1.003	0.0009	0.003	0.001	1.003	0.0013
Orig. to current HPI, 3-digit ZIP	0.008	0.001	1.008	<.0001	0.008	0.001	1.008	<.0001
Seasoning	0.031	0.006	1.03	<.0001	0.035	0.006	1.04	<.0001
Multiple Borrowers	-0.554	0.016	0.58	<.0001	-0.535	0.016	0.59	<.0001
Single Female	-0.163	0.008	0.85	<.0001	-0.171	0.009	0.84	<.0001
Product-type: term	-0.266	0.069	0.77	0.0001	-0.238	0.062	0.79	0.0001
Product-type: tenure	-0.629	0.058	0.53	<.0001	-0.599	0.057	0.55	<.0001
Product-type: modified term	-0.031	0.018	0.97	0.0823	-0.014	0.018	0.99	0.4327
Product-type: modified tenure	-0.113	0.031	0.89	0.0003	-0.096	0.031	0.91	0.0019
Product-type: Line of Credit	0	.	1	.	0	.	1	.
450 or Lower					0.322	0.024	1.38	<.0001
450-500					0.369	0.030	1.45	<.0001
500-550					0.302	0.021	1.35	<.0001
550-580					0.265	0.021	1.30	<.0001
580-600					0.232	0.024	1.26	<.0001
600-620					0.175	0.016	1.19	<.0001
620-640					0.114	0.017	1.12	<.0001
640-660					0.137	0.017	1.15	<.0001
660-680					0.072	0.020	1.08	0.0004
680-700					0.061	0.013	1.06	<.0001
700-720					0.051	0.013	1.05	<.0001
720-740					0.010	0.009	1.01	0.2594
Over 740					0	.	1	.
State FE	51				51			
Borrower Age FE	33 (Ages 63-95)				33 (Ages 63-95)			
Current Loan Year FE	11 (Yrs 2006-2016)				11 (Yrs 2006-2016)			
Pseudo R Squared	0.067				0.068			
C Statistic	0.678				0.680			
N	1,695,893				1,695,893			
Sample Mean of Dep. Var.	0.073							

Excluded categories are: Single-Male, LTV <=60 Line of Credit, current year 2016, State CA, Borrower Age 75, and Credit Score Over 740

Table 7 - Payoff Model

Dependent Variable is Indicator of Loan Being Paid Off
Standard Errors Clustered at the State Level

	Base Model				Credit Model			
	Coef.	Std. Err.	Od. Ratio	Prb>ChiSq	Coef.	Std. Err.	Od. Ratio	Prb>ChiSq
Intercept	3.948	0.329		<.0001	4.253	0.344		<.0001
1.00 <DP LTV<= 60	0	.	1	.	0	.	1	.
2.60 <DP LTV<= 80	-2.008	0.048	0.13	<.0001	-1.921	0.048	0.15	<.0001
3.80 <DP LTV<=100	-3.621	0.107	0.03	<.0001	-3.527	0.112	0.03	<.0001
4.100<DP LTV<=120	-5.537	0.165	0.004	<.0001	-5.428	0.173	0.004	<.0001
5.DP LTV > 120	-7.001	0.317	<0.001	<.0001	-6.853	0.328	0.001	<.0001
T&I Distress Flag	-1.022	0.049	0.36	<.0001	-0.740	0.045	0.48	<.0001
Orig. to DP HPI, 3-digit ZIP	0.005	0.001	1.005	<.0001	0.006	0.001	1.01	<.0001
Last 12 mths HPI, 3-digit ZIP	0.016	0.003	1.016	<.0001	0.017	0.003	1.02	<.0001
Seasoning	0.071	0.033	1.07	0.0309	0.058	0.034	1.06	0.0911
Multiple Borrowers	0.741	0.029	2.10	<.0001	0.709	0.031	2.03	<.0001
Single Female	0.188	0.020	1.21	<.0001	0.210	0.021	1.23	<.0001
Product-type: term	0.441	0.311	1.55	0.1567	0.368	0.301	1.45	0.2201
Product-type: tenure	1.564	0.144	4.78	<.0001	1.492	0.149	4.45	<.0001
Product-type: modified term	0.150	0.046	1.16	0.0013	0.106	0.041	1.11	0.0096
Product-type: modified tenure	0.084	0.073	1.09	0.253	0.050	0.068	1.05	0.461
Product-type: Line of Credit	0	.	1	.	0	.	1	.
450 or Lower					-1.031	0.059	0.36	<.0001
450-500					-0.999	0.064	0.37	<.0001
500-550					-0.922	0.085	0.40	<.0001
550-580					-0.906	0.067	0.40	<.0001
580-600					-0.777	0.057	0.46	<.0001
600-620					-0.889	0.063	0.41	<.0001
620-640					-0.710	0.047	0.49	<.0001
640-660					-0.652	0.058	0.52	<.0001
660-680					-0.517	0.042	0.60	<.0001
680-700					-0.475	0.037	0.62	<.0001
700-720					-0.351	0.036	0.70	<.0001
720-740					-0.296	0.026	0.74	<.0001
Over 740					0	.	1	.
State FE	51				51			
Borrower Age FE	33 (Ages 63-95)				33 (Ages 63-95)			
Due & Payable Year FE	13 (Yrs 2005-2017)				13 (Yrs 2005-2017)			
Pseudo R Squared	0.679				0.687			
C Statistic	0.930				0.933			
N	122,427				122,427			
Sample Mean of Dep. Var.	0.480							

Excluded categories are: Single-Male, LTV <=60, Line of Credit, no T&I Payment Issues, DP year 2015, State CA, Borrower Age 75, and Credit Score Over 740

Table 8 - REO vs TPS or PFS Model

Dependent Variable is Indicator of Adverser Liquidation being an REO

Standard Errors Clustered at the State Level

	Base Model				Credit Model			
	Coef.	Std. Err.	Od. Ratio	Prb>ChiSq	Coef.	Std. Err.	Od. Ratio	Prb>ChiSq
Intercept	-1.031	0.229		<.0001	-1.055	0.217		<.0001
1.00 <DP LTV<= 60	0	.	1	.	0	.	1	.
2.60 <DP LTV<= 80	0.529	0.081	1.70	<.0001	0.528	0.081	1.70	<.0001
3.80 <DP LTV<=100	0.788	0.136	2.20	<.0001	0.786	0.136	2.19	<.0001
4.100<DP LTV<=120	0.970	0.197	2.64	<.0001	0.966	0.198	2.63	<.0001
5.DP LTV > 120	0.984	0.262	2.68	0.0002	0.979	0.263	2.66	0.0002
T&I Distress Flag	0.028	0.045	1.03	0.5375	0.010	0.039	1.01	0.791
Orig. to DP HPI, 3-digit ZIP	-0.001	0.001	1.00	0.1638	-0.001	0.001	1.00	0.149
Last 12 mths HPI, 3-digit ZIP	-0.016	0.002	0.98	<.0001	-0.016	0.002	0.98	<.0001
Seasoning	0.042	0.027	1.04	0.1201	0.044	0.027	1.05	0.1032
Multiple Borrowers	0.053	0.033	1.05	0.1023	0.054	0.032	1.06	0.0895
Single Female	-0.031	0.024	0.97	0.1988	-0.033	0.024	0.97	0.1708
Product-type: term	0.155	0.106	1.17	0.1452	0.158	0.108	1.17	0.1435
Product-type: tenure	-0.190	0.339	0.83	0.5754	-0.188	0.341	0.83	0.5814
Product-type: modified term	-0.019	0.068	0.98	0.7803	-0.017	0.068	0.98	0.8009
Product-type: modified tenure	0.030	0.071	1.03	0.6744	0.030	0.071	1.03	0.6718
Product-type: Line of Credit	0	.	1	.	0	.	1	.
450 or Lower					0.155	0.056	1.17	0.006
450-500					0.129	0.064	1.14	0.0442
500-550					0.082	0.051	1.09	0.1092
550-580					0.007	0.039	1.01	0.8651
580-600					0.011	0.040	1.01	0.7838
600-620					-0.046	0.054	0.96	0.3898
620-640					0.020	0.047	1.02	0.6696
640-660					0.014	0.050	1.01	0.7785
660-680					0.051	0.054	1.05	0.3425
680-700					-0.005	0.036	1.00	0.8918
700-720					0.012	0.047	1.01	0.8009
720-740					0.040	0.039	1.04	0.308
Over 740					0	.	1	.
State FE	51				51			
Borrower Age FE	33 (Ages 63-95)				33 (Ages 63-95)			
Due & Payable Year FE	13 (Yrs 2005-2017)				13 (Yrs 2005-2017)			
Pseudo R Squared	0.0828				0.0832			
C Statistic	0.659				0.659			
N	63,717				63,717			
Sample Mean of Dep. Var.	0.800							

Excluded categories are: Single-Male, LTV <=60, Line of Credit, no T&I Payment Issues, DP year 2015, State CA, Borrower Age 75, and Credit Score Over 740

Table 9 - Severity Model

Dependent Variable is Loss Severity

Measured as Loss as a Percentage of Liquidation UPB (100=Loss equal to 100% of Liquidation UPB)

Standard Errors Clustered at the State Level

	Base Model			Credit Model			Credit Model by Liq. Type		
	Coef.	Std. Err.	Prob>t	Coef.	Std. Err.	Prob>t	Coef.	Std. Err.	Prob>t
Intercept	-0.89	0.69	0.2005	-0.97	0.67	0.146	-1.27	0.64	0.0463
1.00 <DP LTV<= 60	0	.	.	0	.	.	0	.	.
2.60 <DP LTV<= 80	-1.57	0.45	0.0004	-1.58	0.44	0.0004	-1.57	0.44	0.0004
3.80 <DP LTV<=100	-3.08	0.50	<.0001	-3.08	0.50	<.0001	-3.08	0.50	<.0001
4.100<DP LTV<=120	-3.78	0.62	<.0001	-3.79	0.62	<.0001	-3.79	0.62	<.0001
5.DP LTV > 120	-4.71	0.67	<.0001	-4.73	0.67	<.0001	-4.72	0.67	<.0001
T&I Distress Flag	0.13	0.16	0.3998	-0.05	0.16	0.7452	-0.04	0.15	0.7804
distress_flag b) No	0	.	.	0	.	.	0	.	.
Orig. to DP HPI, 3-digit ZIP	0.00	0.00	0.3579	0.00	0.00	0.4203	0.00	0.00	0.3753
Last 12 mths HPI, 3-digit ZIP	-0.04	0.02	0.0437	-0.04	0.02	0.0412	-0.04	0.02	0.039
Seasoning	0.98	0.07	<.0001	0.97	0.07	<.0001	0.98	0.07	<.0001
Multiple Borrowers	-0.89	0.15	<.0001	-0.86	0.14	<.0001	-0.86	0.14	<.0001
Single Female	-0.69	0.08	<.0001	-0.70	0.08	<.0001	-0.70	0.08	<.0001
Product-type: term	0.78	0.45	0.0837	0.81	0.45	0.0726	0.78	0.45	0.0852
Product-type: tenure	-0.42	0.77	0.5856	-0.37	0.77	0.6312	-0.41	0.77	0.5945
Product-type: mod. term	-1.38	0.22	<.0001	-1.35	0.21	<.0001	-1.35	0.21	<.0001
Product-type: mod. tenure	-1.84	0.27	<.0001	-1.80	0.26	<.0001	-1.81	0.27	<.0001
Product-type: Line of Credit	0	.	.	0	.	.	0	.	.
PFS	-7.30	0.48	<.0001	-7.29	0.48	<.0001	-6.60	0.38	<.0001
TPS	-4.61	0.38	<.0001	-4.62	0.38	<.0001	-4.32	0.21	<.0001
REO	0	.	.	0	.	.	0	.	.
450 or Lower				0.70	0.30	0.018			
450-500				0.48	0.23	0.037			
500-550				0.54	0.39	0.1651			
550-580				0.48	0.22	0.0305			
580-600				0.66	0.20	0.0008			
600-620				0.76	0.29	0.0093			
620-640				0.29	0.23	0.1949			
640-660				0.27	0.26	0.2866			
660-680				0.18	0.16	0.274			
680-700				0.14	0.19	0.4643			
700-720				0.07	0.16	0.6773			
720-740				0.10	0.19	0.6222			
Over 740				0	.	.			
PFS and 450 or Lower							-1.97	0.70	0.0049
PFS and 450-500							-2.33	0.65	0.0003
PFS and 500-550							-1.85	0.48	0.0001
PFS and 550-580							-0.79	0.25	0.0013
PFS and 580-600							0.54	0.44	0.2194
PFS and 600-620							-1.10	0.63	0.0799

PFS and 620-640			-0.79	0.29	0.0074
PFS and 640-660			-1.07	0.59	0.0667
PFS and 660-680			-0.52	0.34	0.1298
PFS and 680-700			-0.12	0.48	0.802
PFS and 700-720			-0.23	0.22	0.3037
PFS and 720-740			0.05	0.28	0.8616
PFS and Over 740			0	.	.
TPS and 450 or Lower			0.19	0.35	0.592
TPS and 450-500			0.52	0.40	0.1894
TPS and 500-550			-2.92	3.20	0.3614
TPS and 550-580			0.91	0.49	0.0637
TPS and 580-600			0.23	0.52	0.6577
TPS and 600-620			0.80	0.63	0.2048
TPS and 620-640			0.24	0.30	0.4208
TPS and 640-660			-0.19	0.24	0.4282
TPS and 660-680			0.53	0.48	0.268
TPS and 680-700			0.22	0.48	0.649
TPS and 700-720			0.41	0.50	0.4176
TPS and 720-740			0.29	0.45	0.5143
TPS and Over 740			0	.	.
REO and 450 or Lower			0.94	0.34	0.0064
REO and 450-500			0.67	0.27	0.0125
REO and 500-550			1.19	0.23	<.0001
REO and 550-580			0.53	0.26	0.0411
REO and 580-600			0.74	0.25	0.0029
REO and 600-620			0.92	0.30	0.0025
REO and 620-640			0.40	0.27	0.1319
REO and 640-660			0.47	0.31	0.1263
REO and 660-680			0.20	0.18	0.267
REO and 680-700			0.16	0.22	0.4616
REO and 700-720			0.06	0.16	0.7287
REO and 720-740			0.08	0.21	0.6881
REO and Over 740			0	.	.
State FE	51	51	51		
Borrower Age FE	32 (Ages 64-95)	32 (Ages 64-95)	32 (Ages 64-95)		
Due & Payable Year FE	13 (Yrs 2005-2017)	13 (Yrs 2005-2017)	13 (Yrs 2005-2017)		
R Squared	0.1711	0.1713	0.1721		
N	48,364	48,364	48,364		
Sample Mean of Dep. Var.		8.30			

Excluded categories are: Single-Male, LTV <=60, no T&I Payment Issues, Line of Credit, DP year 2015, State CA, Borrower Age 75, and Credit Score Over 740

Table 10 - Effect of Removing Loans with Credit Score below 620

Loans with Credit Information											
	Number of Loans								Dollar Amount ($Mn)		
Origination Year	Active	Paid Off	Assigned	Adv. Terminations	PFS	REO	TPS	Total	Origination	Current	Net Loss
2005	10,608	10,395	5,529	7,539	571	6,168	800	34,071	$2,993	$2,004	$87
2006	19,693	12,723	2,787	12,082	907	9,832	1,343	47,285	$4,405	$3,876	$155
2007	37,827	16,305	1,037	18,661	1,712	14,878	2,071	73,830	$7,348	$6,829	$232
2008	46,313	18,638	1,276	19,210	1,664	15,287	2,259	85,437	$9,068	$8,154	$222
2009	20,481	9,327	1,581	6,253	579	4,854	820	37,642	$4,919	$4,543	$73
Total	134,922	67,388	12,210	63,745	5,433	51,019	7,293	278,265	$28,732	$25,406	$768
Loans with Min. Credit Score 620											
Origination Year	Active	Paid Off	Assigned	Adv. Terminations	PFS	REO	TPS	Total	Origination	Current	Net Loss
2005	8,568	8,869	4,787	5,444	444	4,399	601	27,668	$2,394	$1,664	$62
2006	15,917	10,861	2,372	8,777	703	7,058	1,016	37,927	$3,473	$3,192	$111
2007	29,379	13,698	869	13,119	1,271	10,379	1,469	57,065	$5,607	$5,416	$159
2008	34,554	15,508	1,024	12,599	1,205	9,889	1,505	63,685	$6,755	$6,257	$143
2009	15,868	7,924	1,306	4,141	428	3,167	546	29,239	$3,860	$3,656	$47
Total	104,286	56,860	10,358	44,080	4,051	34,892	5,137	215,584	$22,088	$20,185	$522
Difference (With Min. Credit 620 - with Credit)											
Origination Year	Active	Paid Off	Assigned	Adv. Terminations	PFS	REO	TPS	Total	Origination	Current	Net Loss
2005	-2,040	-1,526	-742	-2,095	-127	-1,769	-199	-6,403	-$599	-$340	-$25
2006	-3,776	-1,862	-415	-3,305	-204	-2,774	-327	-9,358	-$932	-$684	-$44
2007	-8,448	-2,607	-168	-5,542	-441	-4,499	-602	-16,765	-$1,741	-$1,413	-$73
2008	-11,759	-3,130	-252	-6,611	-459	-5,398	-754	-21,752	-$2,313	-$1,897	-$78
2009	-4,613	-1,403	-275	-2,112	-151	-1,687	-274	-8,403	-$1,059	-$887	-$26
Total	-30,636	-10,528	-1,852	-19,665	-1,382	-16,127	-2,156	-62,681	-$6,644	-$5,221	-$246
Percentage Difference (With Min. Credit 620 - with Credit)											
Origination Year	Active	Paid Off	Assigned	Adv. Terminations	PFS	REO	TPS	Total	Origination	Current	Net Loss
2005	-19.2%	-14.7%	-13.4%	-27.8%	-22.2%	-28.7%	-24.9%	-18.8%	-20.0%	-17.0%	-28.7%
2006	-19.2%	-14.6%	-14.9%	-27.4%	-22.5%	-28.2%	-24.3%	-19.8%	-21.2%	-17.6%	-28.5%
2007	-22.3%	-16.0%	-16.2%	-29.7%	-25.8%	-30.2%	-29.1%	-22.7%	-23.7%	-20.7%	-31.4%
2008	-25.4%	-16.8%	-19.7%	-34.4%	-27.6%	-35.3%	-33.4%	-25.5%	-25.5%	-23.3%	-35.4%
2009	-22.5%	-15.0%	-17.4%	-33.8%	-26.1%	-34.8%	-33.4%	-22.3%	-21.5%	-19.5%	-35.6%
Total	-22.7%	-15.6%	-15.2%	-30.8%	-25.4%	-31.6%	-29.6%	-22.5%	-23.1%	-20.5%	-32.1%

All HECM Loans in Book

	Active	Paid Off	Assigned	Adv. Terminations	PFS	REO	TPS	Total	Origination	Current	Net Loss
Total	181,435	171,961	42,266	96,803	7,846	77,736	11,221	589,268	$43,983	$34,571	$1,195
Total for Counter	140,238	145,096	35,855	66,918	5,850	53,164	7,904	456,532	$33,812	$27,467	$812
Change	-41,197	-26,865	-6,411	-29,885	-1,996	-24,572	-3,317	-132,736	-$10,171	-$7,104	-$383