An Analysis of Default Risk in the Home Equity Conversion Mortgage (HECM) Program

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Abstract

While reverse mortgages are intended as a tool to enable financial security for older homeowners, in 2014, nearly 12 percent of reverse mortgage borrowers in the federally insured Home Equity Conversion Mortgage (HECM) program were in default on their property taxes or homeowners insurance. Unlike the traditional mortgage market, there were no risk-based underwriting guidelines for HECMs through 2013. In response to the relatively high default rate, a variety of policy responses were implemented in 2013, including establishing underwriting guidelines. However, there is a lack of data and analysis to inform such criteria. Our analysis follows 30,000 seniors counseled for reverse mortgages between 2006 and 2011. The data includes comprehensive financial and credit report attributes, not typically available in analyses of reverse mortgage borrowers. Using a bivariate probit model that accounts for selection, we estimate the likelihood of tax and insurance default. Financial characteristics that increase default risk include the percentage of funds withdrawn in the first month of the loan, a lower credit score, higher property tax to income ratio, low or no unused revolving credit, and a history of being past due on mortgage payments or having a tax lien on the property. Our estimate of the elasticity of default with respect to credit scores is similar to that for closed-end home equity loans, but higher than that for HELOCs. We simulate the effects of alternative underwriting criteria and policy changes on the probability of take-up and default. Reductions in the default rate with a minimal effect on participation can be achieved by requiring that participants with low credit scores set aside some of their HECM funds for future property tax and insurance payments, a form of escrowing.

1. Introduction

Home equity is an illiquid asset that can typically only be extracted through a home sale or mortgaging the property. However, reverse mortgages provide a mechanism for senior households to withdraw equity from their home without a home sale or monthly mortgage payments. The most prevalent form of reverse mortgage in the U.S., comprising more than 95 percent of the market since the mid-2000s, is the U.S. Department of Housing and Urban Development's (HUD) federally insured Home Equity Conversion Mortgage (HECM). While only about two percent of eligible seniors in the U.S. have reverse mortgages, the volume of HECMs has increased substantially in the past decade; 80 percent of HECM loans have been originated since 2006 (CFPB 2012). HUD's objective for the HECM program is to provide seniors with a vehicle to "supplement social security, meet unexpected medical expenses and make home improvements" (U.S. Department of Housing and Urban Development 2006). The primary obligations for the homeowner are upkeep of the home, and paying property taxes and homeowner's insurance.

As of June 30, 2014, 12.04 percent of all active HECM loans were in technical default for not paying property taxes or homeowner's insurance (Integrated Financial Engineering 2014), placing nearly 78,000 senior homeowners at risk of foreclosure.[1] Further, the portion of HUD's Mutual Mortgage Insurance (MMI) fund backing the HECM program is estimated to have the value of negative $1.2 billion (Department of Housing and Urban Development 2014). These issues have prompted a series of policy changes to increase the solvency of the HECM program. One of the most substantial changes is a requirement for lenders to underwrite HECMs taking into account borrower financial and credit risk characteristics (Mortgagee Letter 2013-28; Mortgagee Letter 2014-22). While these underwriting guidelines are a standard component of forward mortgage lending, the introduction of such criteria for HECMs is new.

A significant challenge for the reverse mortgage market is to establish criteria knowable at the time of origination to reduce default risk while not unnecessarily excluding households from the market. Several factors have been anecdotally associated with higher rates of default; however, there has been no systematic analysis to date of borrower attributes and program characteristics that contribute to tax and insurance default among reverse mortgage borrowers due to the lack of comprehensive data. For example, it is unknown the extent that factors such as credit scores, debt, or income are significant

[1]According to the IFE (2014) analysis, there were 647,737 active HECM loans through June 30, 2014.

predictors of tax and insurance default among reverse mortgage borrowers, as credit and income data were not previously collected.

Understanding the causes of default for reverse mortgage contracts extends the wider mortgage default literature. Higher initial withdrawals on HECM loans may increase default risk, similar to findings of increased default risk among borrowers with higher loan to value (LTV) ratios in the forward market. However, negative equity which is a primary determinant of default in the forward market has a different effect for reverse mortgages. Unlike forward mortgages, the federal mortgage insurance on the HECM covers any negative difference between the loan amount and current house value, reducing the incentive for borrowers to strategically default when the loan is underwater. Having the ability to make mortgage payments is not relevant for HECMs as it is for forward mortgages; however, future HECM underwriting may consider the ability to afford ongoing property tax and insurance payments. Home equity credit line availability also differs for reverse and forward mortgages; unlike Home Equity Lines of Credit (HELOCs), untapped HECM funds cannot be cancelled by the lender in response to negative macroeconomic and house price shocks. The likely result is different equity extraction behaviors and implications for default.

Our analysis informs this research gap, using a unique dataset of more than 30,000 seniors counseled for reverse mortgages between 2006 and 2011, 58 percent of whom obtained HECM loans. The data include comprehensive financial and credit report attributes at the time of origination. In partnership with HUD, we link these data to loan-level HECM data containing information on originations, withdrawals, and tax and insurance default outcomes. Our analysis builds on a small body of existing literature modeling reverse mortgage take-up (e.g. Davidoff and Welke 2007; Davidoff 2013; Shan 2011; Haurin et al. 2014) and terminations (e.g. Szymanoski et al. 2007; Bishop and Shan 2008; Davidoff 2013). However, with the exception of the actuarial report prepared for HUD (Integrated Financial Engineering (IFE) 2011; 2012; 2013; 2014), the previous literature does not model the probability of tax or insurance default. Further, previous analyses, including the actuarial reports, lack many important characteristics of borrowers at the time of origination, including income, debt, and credit report attributes that we include in our analysis. To inform our expectations about how these characteristics may default for reverse mortgage borrowers, we draw from the extensive literature on mortgage default in the forward market.

Our model takes into account multiple decisions, including the initial decisions of a senior whether to obtain a HECM and if yes, the initial withdrawal percentage. Default is modeled as a third decision, which is observed for borrowers up to the end of the sample period or termination of the loan. These three decisions are modeled as a bivariate probit model with sample selection, where the initial withdrawal percentage is treated as an endogenous variable. We conclude our analysis with a series of simulations to evaluate the potential impact of credit-based underwriting criteria, in conjunction with limits to initial withdrawals and lifetime set-asides for property taxes and insurance.

Our results suggest a statistically significant relationship between future default and credit report indicators, including the credit score, prior delinquency on mortgage debt, and tax liens. A positive relationship is found between default and the property tax burden. Even after controlling for risk characteristics, the initial withdrawal percentage is an important factor predicting default. This finding extends prior research linking leverage to mortgage default in the forward market. We also find evidence supporting a consumption smoothing hypothesis—HECM borrowers with high property taxes relative to income have lower initial withdrawals. Tax burdened borrowers are more likely to withhold a portion of their available HECM proceeds for future periods to pay for expected high property taxes, thus enabling them to maintain their current level of consumption.

The simulations indicate that default risk can be reduced with minimal effect on program participation by establishing a minimum credit score criterion. They further suggest that additional reductions in default can be achieved by requiring selected households to set aside HECM funds received at the time of origination, these dedicated to paying future property tax and insurance costs.

2. Policy Background

HECMs are non-recourse loans and the amount owed is not repaid until the borrowers die, sell the home, or a foreclosure occurs. At the termination of the reverse mortgage, borrowers (or their heirs) are responsible to pay the lesser of the current balance of the HECM or 95 percent of the then appraised value. After repaying the HECM balance, any proceeds from the sale of the home belong to the borrowers or their heirs. HECMs are insured by the Federal Housing Administration (FHA) through the mutual mortgage insurance (MMI) fund, which fully protects borrowers and lenders against crossover risk, which is the risk that the balance of the loan grows to exceed the value of the home. Borrowers retain title to the property throughout their residence and are responsible for property taxes, homeowners insurance, and other assessments on the property.

If a borrower fails to pay property taxes or homeowner's insurance, the lender is notified (as a lien holder) and if there are untapped HECM funds (e.g. in the line of credit), the lender can make the payments on behalf of the borrower. [2] However, if the borrower has exhausted all available HECM funds, the borrower is considered in "technical default" on the HECM. The lender is required to make a "corporate advance" of funds to pay the past due obligations, adding the amount advanced to the borrower's HECM loan balance and working with the borrower to repay the funds. Further, the lender could offer to refinance the HECM loan into a new HECM if the home value increased substantially since the time of origination. In the absence of repayment or a workout plan, the lender is required to request permission from HUD to accelerate the loan, thereby making it "due and payable," which could lead to eventual foreclosure.[3] As of June 30, 2014, 12 percent of active HECMs were in technical default due to failure to pay property taxes and homeowner's insurance (Integrated Financial Engineering 2014).

Technical defaults in the HECM program can lead to increased risks and costs for the lender, the federal government and the homeowner. The lender servicing the mortgage incurs costs as they seek to work out a solution with the borrower; if they fail to work out a solution or accelerate the property in a timely manner, they may lose the HUD insurance for the loan and be required to assume the debt. To the extent that the default causes the foreclosure of a property in a negative equity position, the federal MMI fund assumes the loss, which likely would have been less severe had the termination of the mortgage occurred through an arms-length sales transaction rather than a foreclosure. Finally, for the borrower, foreclosure is antithetical to the underlying policy intent of the program--to enable senior homeowners to have increased financial stability while remaining in their homes.

Under the authority of Congress, HUD is permitted to establish rules that structure HECM product options for borrowers in line with the policy intent, while maintaining the solvency of the program (for example, see Mortgagee Letters 2013-27; 2013-28; 2013-33). The first set of rules includes those that affect borrower eligibility. To be eligible for a HECM, the youngest borrower must be at least

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[2]The amount of available HECM funds is not based on the current value of the property, but rather the initial loan amount adjusted for growth, less any prior withdrawals. Subsequent changes in property values are not accounted for in this determination. Thus, loan proceeds may be available even if the current property value is less than the current loan balance. In contrast, loan proceeds may not be available even if the current property value greatly exceeds the loan balance due to house price appreciation.

[3] To maintain the loan in good standing with HUD, and thus available for assignment, the lender must follow HUD guidelines regarding payment of property taxes and insurance, and request permission from HUD to call the loan due and payable (acceleration) when such obligations are not met. Once approved for acceleration, the servicer will issue a due and payable notice to the borrower. The issuance of this notice may motivate the borrower to cure the default; if not, a notice of intent to foreclose will be issued and, after six months, legal action of foreclosure must be taken.

62 years of age and live in the home as their principal residence.[4] The HECM can be the only lien on the property. Any existing mortgages or liens must be paid in full with the proceeds of the HECM or in cash prior to origination. Because of the complexities of the mortgage product, potential HECM borrowers must receive counseling from a HUD approved agency prior to application for a loan. Historically, HUD has not imposed any additional underwriting criteria (e.g., related to credit score, debt or income). However, beginning in March of 2015, HUD requires lenders to assess and document a borrower's "ability to pay" before originating a loan, following minimum credit, debt and affordability standards (Mortgagee Letter 2013-28; Mortgagee Letter 2014-22).

Borrowers failing to meet the new underwriting criteria can be denied a HECM, or can be required to set aside a portion of their available principal in a lender managed escrow account to cover future property tax and insurance obligations, called a life expectancy set-aside (LESA). Thus, in addition to having sufficient funds available through the HECM to pay off existing mortgage debt, borrowers failing to meet the underwriting criteria also need to have sufficient money available through the HECM loan proceeds or in cash to fund the tax and insurance LESA. The implications of these policy changes are unclear. The overall default rate for the program should fall. However, it is unclear what proportion of borrowers falling below the underwriting thresholds will have sufficient equity to fund the set aside, in addition to paying off their mortgage debt and other obligations. To understand this tradeoff of participation rate and default rate, our analysis explores the impact of different credit thresholds and LESA requirements on both take-up and default rates.

The second set of policy rules include those that affect the use of HECM proceeds. The amount of money that a borrower can access from a HECM, or principal limit, is the product of HUD's principal limit factor multiplied by the maximum claim amount (MCA). The MCA is the lesser of the appraised value on the home or the HECM loan limit. The HECM loan limit increased over time to a nationwide limit of $625,000 in February, 2009. HUD sets the PLF as a function of the borrower's age and the expected interest rate, based on the estimated growth of the balance on a HECM (principal plus accrued interest) over the expected lifetime of the loan. The balance is expected to grow up to but not exceed the MCA, as HUD assumes liability for HECMs with loan balances greater than 98 percent of the MCA and must pay for any shortfalls out of the MMI fund.

[4] Additional details are in Haurin et al. (2014) and Moulton et al. (2014).

The proceeds from a HECM loan can be distributed to borrowers through a variety of different payment structures: a lump-sum at origination, a line of credit, "tenure" payments (a lifetime annuity), and "term" payments (a fixed payment for a specified number of years), or some combination of these options. Borrowers taking out a fixed rate HECM are forced to take all money as a lump sum at closing. However, drawing all funds at closing may increase default risk to borrowers, who have no available funds in the HECM to draw from if needed, and may increase the crossover risk to the program. Due in part to this increased risk, HUD placed a moratorium on the standard fixed rate-full draw HECM product in 2013 (Mortgagee Letter 2013-1). This was a substantial policy change, as this option had come to dominate the market, growing from less than 10 percent in early 2009 to 70 percent of the market by 2012 (for more details on the reasons for this trend, see CFPB 2012). Further, in 2013, HUD issued a new rule restricting the withdrawal amount in the first year to 60 percent of the initial principal limit, with a provision for higher amounts if needed to payoff mandatory obligations, primarily existing mortgages (Mortgagee Letter 2013-27. 2013). The initial withdrawal restriction is intended to reduce default risk; however, the actual impact of the initial withdrawal amount on tax and insurance default is unknown.

3. Existing Literature

There are two bodies of related literature on reverse mortgages that have some relevance for tax and insurance default outcomes. First, there is a small body of research that considers factors associated with the take-up of reverse mortgages. These studies are relevant in that a household can default on a HECM only if it has previously obtained a HECM, and observed and unobserved factors that lead a household to take a HECM may also be associated with default. Using HUD loan level data on reverse mortgage borrowers from 1995-2005 and U.S. Census data from 2000, Shan (2011) estimates the take-up rate for reverse mortgages at the zip code level. She finds that zip codes with lower incomes, higher home values, higher owner costs relative to income, higher levels of education, higher proportion of minority residents and lower average credit scores are associated with a higher reverse mortgage take-up rate.

Recent work by Haurin et al. (2014) finds that house price dynamics are also an important factor; a higher proportion of homeowners take-out reverse mortgages in states where house prices are high relative to the long term average and where house prices are more volatile, suggesting that seniors may take reverse mortgages to lock-in home equity. This finding extends prior work by Nakajima and Telyukova (2013), who estimate the demand for reverse mortgages will be greater when there is house price uncertainty, as reverse mortgages can serve as a hedge against house price risk. Nakajima and

Telyukova also estimate that homeowners with higher health care costs will be more likely to take out reverse mortgages to help cover medical expenditures. Davidoff (2014) finds that neighborhoods with a higher minority concentration tend to have higher rates of HECM borrowing; however, he notes that there is a correlation between neighborhoods with volatile house prices and a high proportion of minority residents. Taken together, these studies suggest that reverse mortgage borrowers are more likely to be financially constrained and have relatively low incomes.

Second, there are several empirical studies that examine termination and assignment outcomes in the HECM program. While tax and insurance default is not a terminal outcome, it can lead to termination and prevent loan assignment. Understanding factors associated with these outcomes indirectly informs tax and insurance default. In an early study, Rodda et al. (2004) model terminations using 1990-2000 HECM data and find that significant explanatory variables include borrower age, income at the time of origination, gender, presence of a co-borrower, house price growth, and the spread between 30 year and one-year Treasury bills. Not significant are the amount of borrower assets or home equity at the time of origination. Szymanoski et al. (2007) report the hazard rates of termination by borrower, and type of borrower (couple or gender if single). They found that the average duration of a reverse mortgage was seven years, with a 10 year survival rate of only 22 percent. Couples tend to terminate more quickly, followed by single males. In their study of terminations, Bishop and Shan (2008) find similar results by marital status and gender. Shan (2011) extends the empirical model and finds that an increase in initial house value and the house price appreciation rate in the locality are positively associated with termination, suggesting that HECM borrowers may sell their homes or refinance to tap additional equity when housing values increase.

Using data from the American Community Survey and HUD's reverse mortgage database, Davidoff and Welke (2007) find that HECM borrowers tend to terminate their mortgages and exit their homes more quickly than otherwise similar non-HECM senior homeowners. They suggest that reverse mortgage borrowers may be heavy discounters who have a stronger desire to extract home equity, both through a reverse mortgage and through sale when housing values increase. This runs counter to expectations of adverse selection in the HECM program, where borrowers who expect to stay in their homes longer enter into reverse mortgages, taking advantage of the insurance feature of the product (Shiller and Weiss 2000; Miceli and Sirmans 1994). In subsequent work, Davidoff (2013) also finds that HECM borrowers do not appear to behave ruthlessly by exercising their "put option," allowing credit line funds to grow at a rate that is higher than their home appreciation and then drawing the remaining funds immediately prior to termination.

The only empirical analysis of tax and insurance default in the HECM program is that by IFE in their actuarial reports prepared for HUD (IFE 2011; 2012; 2013; 2014). The reports find that defaults are more likely the greater the initial withdrawal, the younger the borrower, for single borrowers, for property located in Florida, Texas, and California, and for a longer time since origination.[5] They also find that default likelihood is lower if the dwelling's value is above the area median home value and if the borrower selects a fixed rate, full draw loan (IFE 2012). While the IFE analysis provides some information about characteristics associated with technical default, the data set is limited and important borrower characteristics such income, assets, and credit score were not collected. Further, the IFE analysis does not take into account the selectivity of the HECM population.[6] Finally, the IFE study treats the initial withdrawal amount as exogenous; however, unobserved factors that are associated with higher draw amounts may also be associated with tax and insurance defaults. Our analysis helps address these deficiencies by including a broader array of borrower characteristics likely associated with default, and by accounting for the selection process into a HECM and the resulting partial observability of the initial withdrawal and default.

4. Theoretical Expectations and Model

4.1 Theoretical Expectations

We form our expectations about property tax and insurance default for reverse mortgages by drawing from prior literature on mortgage default in the forward market. In the forward mortgage market, default is typically framed through an options theoretic model, where households optimally exercise their embedded options to put (default) or call (prepay) their mortgage, based in large part on the value of the home and the balance of the mortgage. As house prices increase, forward mortgage borrowers are more likely to prepay their mortgage to realize equity gains through home sale or refinancing. The same is true for HECM borrowers; as house prices increase, HECM borrowers may exercise the option to sell the home and terminate the reverse mortgage or refinance into another reverse mortgage to tap additional equity.

[5] The average default occurs in the third year after origination (IFE 2013).

[6] A similar problem was identified in the forward mortgage market by Ross (2000), who was estimating default probabilities.

For forward mortgage borrowers, ruthlessly exercising the default option when house prices decline may be more attractive than realizing a substantial financial loss, particularly under conditions of negative equity (Vandell 1995; Deng et al. 2000). Prior empirical studies have found negative equity to be a significant predictor of mortgage default (Foote et al. 2008; Mayer et al. 2009; Elul et al. 2010). For HECM borrowers, the federal insurance covers any shortfall between home value and the balance on the mortgage. Thus, unlike forward mortgages, there is no strategic incentive for HECM borrowers to default under conditions of negative equity. A reverse mortgage borrower behaving ruthlessly may actually have an incentive to stay in the home longer under conditions of negative equity (Davidoff and Welke 2007), potentially underinvesting in the maintenance of the home (Shiller and Weiss 2000; Miceli and Sirmans 1994; Davidoff 2013).

A complimentary perspective on mortgage default is the trigger events model (Vandell 1995; Ambrose and Capone 1998; Elmer and Seelig 1999), where default occurs because of a negative shock to the household post-origination, such as loss of income or increased medical expenses. Declines in house prices can compound the default probability in the presence of a triggering event, as a household facing a triggering event might otherwise be able to extract equity (e.g., through sale) to help compensate for the loss, or relocate to reduce housing costs. For example, senior homeowners experiencing a shock (e.g. loss of a spouse or increase in property tax rates) may desire to move to a location with lower property related costs (Shan 2010). To the extent that HECM borrowers experience declines in house prices, they may be less able to relocate and more likely to default on (high) property related costs.

Even for post-origination shocks, observable characteristics at the time of origination may identify which households are relatively more likely to encounter a shock and may describe a household's ability to endure an economic shock. The financial position of a household at origination, including cash flow deficiencies, liquidity constraints and poor credit management, have been found to be important predictors of default in the forward market (Avery et al 1996; Pennington-Cross 2003; Foote, Gerardi and Willen 2008; Elul et al. 2010; Demyanyk and Van Hemert 2011).

Cash flow deficiencies in the forward mortgage market are typically measured by debt to income ratios, including the mortgage payment as a percent of monthly income (Archer et al. 1996). High debt to income ratios can increase vulnerability to future trigger events, but can also indicate inability to afford a loan from the time of origination. In analysis of subprime mortgage loans, researchers have found that excessive mortgage payment burdens exacerbated default risk (Mayer et al. 2009). In the HECM market, there has historically been no analysis of borrowers' cash flow. Borrowers could even be delinquent on their dwelling's property taxes and insurance at the time of origination, as long as the proceeds from the HECM were sufficient to bring any past due amounts current. Thus, high property tax and insurance payments relative to income may be associated with increased risk of default.

In the presence of a negative income shock or trigger event, households often can, at least temporarily, finance consumption and mandatory obligations from savings, borrowing, or other forms of wealth (Elmer and Seelig 1999). Households with lower levels of non-housing wealth have fewer resources to draw from in the presence of a shock. Liquidity indicates the ability of a household to borrow to finance consumption (Agarwal et al. 2007). Thus, households that are wealth constrained and liquidity constrained are more likely to experience default in the forward mortgage market (Elul et al. 2010). In general, we expect that HECM borrowers are more illiquid and have fewer non-housing assets than other senior households (Shan 2011; Nakajima and Telyukova 2013). Home equity is often the primary asset and source of capital for seniors, motivating equity extraction through HECM borrowing in the first place (Mayer and Simmons 1994; Hurst and Stafford 2004). Thus, we expect that HECM borrowers with relatively high non-housing wealth and revolving credit availability at the time of origination to be less likely to default on property taxes and insurance.

Further, the lumpy nature of property tax and insurance payments-- infrequent amounts due once or twice per year-- may increase default risk for HECM borrowers. Property tax and insurance payments for HECM borrowers are not escrowed as part of a monthly mortgage payment as is common in the forward market. A lumpy property tax or insurance payment may create a liquidity problem for households with little wealth and credit availability. A study by Anderson and Dokko (2011) finds that subprime borrowers, who lacked escrows for property taxes and homeowners insurance, were more likely to experience early delinquency on their mortgage payments immediately following their property tax due dates. There is some evidence of lower property delinquency rates in taxing jurisdictions that bill more frequently and in smaller increments (Waldhart and Reschovsky 2012).

Prior research suggests that senior households with lower levels of financial literacy and planning may have difficulty making financial decisions (Lusardi and Mitchell 2007; 2011). In the default literature, prior credit payment histories and credit scores at the time of origination have been a persistent predictor of mortgage default even after accounting for negative equity, financial resources, and exposure to trigger events (Avery et al. 1996; Pennington-Cross 2003). We expect that households in the HECM program who exhibit prior histories of poor financial planning (e.g., lower credit scores or prior missed payments) are more likely to default on their property taxes and insurance.

A final aspect of the HECM program that may be associated with default risk is the amount of available proceeds withdrawn near the time of origination. There are at least two reasons why an increase in the initial withdrawal may be associated with increased default. First, an increase in equity withdrawn at closing increases total leverage, reducing the amount of untapped HECM funds and increasing the risk of entering technical default if the borrower fails to pay property taxes or homeowner's insurance. In the forward market, research on equity extractions finds a strong association between initial leverage amounts and default (Mian and Sufi 2011; Laufer 2011; Kumar 2014).

Second, the initial withdraw amount is a choice borrowers make to manage their consumption needs over the longer term. Those who anticipate future expenses may choose to draw less initially to smooth consumption in future periods. While borrowers could choose to save a portion of the initial equity withdrawn for future consumption, prior research suggest that this is not likely, as borrowers tend to consume rather than save lumpy infusions of cash (Agarwal et al. 2007). Further, the growth rate on the HECM makes it financially advantageous to store unused equity in the line of credit. There is some evidence of consumption smoothing behavior among HELOC borrowers (Dey 2005). Agarwal et al. (2006a) finds that borrowers with lower credit scores withdraw a lower proportion of available equity at origination in line with expectations of future credit shocks. For HECM borrowers, a similar analogy might be expectations regarding future property tax expenses. To the extent that HECM borrowers expect to be constrained in paying for property taxes, they may withdraw less initially to help smooth their consumption in future periods. We expect property tax to income burden to be negatively associated with the initial withdraw proportion, but positively associated with default.

4.2 Empirical Model

The purpose of our empirical analysis is to identify factors at the time of origination that are associated with future property tax and insurance default, conditioned on a household having obtaining a HECM and the amount of funds withdrawn up-front (withdrawal percentage). The decision to obtain a HECM and default are binary outcomes, while the withdrawal percentage is a continuous outcome.[7]

[7] We treat technical default as a binary outcome rather than modeling it as a competing risk with prepayment or refinancing. We do not treat prepayment as a competing risk, as it is unlikely that a household would sell the home and move to avoid a technical default, given the transaction costs of moving, the fact that a move would terminate the HECM and forfeit the insurance aspect of the HECM loan, and the fact that a technical default is not a foreclosure and can be cured through a workout with the lender. We do not treat refinancing as a competing risk, as declines in home values and reductions to the PLF during our sample period negated the viability of this option. However, we recognize that households who terminate their loans have a shorter exposure time for technical

Whether a household defaults and the withdrawal percentage is observed only if the household obtains a HECM.

Unobserved characteristics that contribute to obtaining a HECM and the withdrawal percentage may be correlated with default propensity. For example, consider a household with significant financial constraints at the time when a decision is made regarding whether to obtain a HECM. Further assume that there is a positive correlation between obtaining a HECM, high withdrawal percentages and subsequent default. Part of this correlation may be explained by observable variables. However, other factors may be unobservable such as the household having a tendency to quickly spend all liquid assets in its possession or other poor credit management behaviors. Thus, we allow the error terms in the three equations to be correlated.

We use a bivariate probit model with sample selection to model default, given that households have a choice to select into a HECM. We estimate the take-up, default, and withdrawal equations simultaneously.

- HECM selection

$$y_{i1}^{*} = x_{i1}'\beta_1 + z_i'\alpha_1 + u_{i1} \tag{1}$$

The household selects a HECM ($y_{i1} = 1$) if $y_{i1}^{*} > 0$ and does not take up HECM otherwise.

- Default

$$y_{i2}^{*} = x_{i2}'\beta_2 + z_i'\alpha_2 + w_i\gamma + u_{i2} \tag{2}$$

The household defaults on tax or insurance ($y_{i2} = 1$) if $y_{i2}^{*} > 0$ and $y_{i1} = 1$. w_i is the initial withdrawal variable.

- Withdrawal

$$w_i = x_{i3}'\beta_3 + z_i'\alpha_3 + u_{i3} \tag{3}$$

In (1)-(3), z_i are the common regressors, and x_{i1}, x_{i2}, x_{i3} are the regressors unique in the respective equation, which ensure that the model is well identified. The unobservables $\begin{bmatrix} u_{i1} & u_{i2} & u_{i3} \end{bmatrix}$ are jointly normal with mean 0 and variance

default (sample truncation). We therefore include an exposure term that is equal to the time of counseling until termination or the last date observed in the data. Further, we are unable to measure default using a proportional hazards model due to data constraints; we only observe the time of default for about half of the observations in our sample.

$$\Sigma = \begin{bmatrix} 1 & \rho_{12} & \rho_{13}\sigma \\ \rho_{12} & 1 & \rho_{23}\sigma \\ \rho_{13}\sigma & \rho_{23}\sigma & \sigma^2 \end{bmatrix}. \tag{4}$$

The unobservables are assumed to be independently and identically distributed between individuals and independent from the regressors x_{i1}, x_{i2}, x_{i3}, z_i. The initial withdrawal is endogenous if $\rho_{13} \neq 0$ or $\rho_{23} \neq 0$. For the derivation of the likelihood function, see Appendix A.

The set of explanatory variables included in the regressions is based on our expectations described above, with specific variables described in the next section. We include state fixed effects in each equation. In the take-up equation, they capture differences in variations in state laws or the average distance to counselors or lenders' offices. State fixed effects in the default equations capture differences in state laws regarding defaults and geographically based lender practices.[8] We also include year dummies in each equation to capture the effect of common macro factors. For the take-up equation, year dummies are at the time of counseling. For the withdrawal and default equations, year dummies are at the time of loan origination.

5. Data and Descriptive Statistics

Our primary dataset consists of confidential reverse mortgage counseling data on households counseled by a large nonprofit housing counseling organization (CredAbility, dba ClearPoint Credit Counseling Services) for the years 2006 to 2011. These data include demographic and socio-economic characteristics of the counseled household. The counseling data also contains Equifax credit report attribute data at the time of counseling, obtained by the nonprofit agency with client consent for counseling and evaluation purposes. The credit report data includes credit score, outstanding balances and payment histories on revolving and installment debts, and public records information.

In addition to data at the time of counseling, our analysis includes detailed data on HECM loan transactions from HUD. Household level data is linked to HECM loan data, including details on origination, withdrawals, terminations and tax and insurance defaults. Importantly, this allows us to account for selection by modeling the take-up of HECMs among counseled households, and

[8]An alternative specification is to re-estimate the entire system of equations by state or region, thus exploring possible heterogeneous effects of model variables by geographic area. However, we lack adequate sample size to estimate the full system of equations across all regions (e.g. the number of observed defaults becomes relatively small), resulting in convergence problems. We are able to estimate the model when we divide our sample into two regions (west and south regions, and midwest and northeast regions), and find that our primary results are stable.

subsequently whether they default on their mortgages. To account for macroeconomic characteristics at the time of origination, we include variables describing recent state-level economic growth and house price volatility and deviations from the historical state-level mean real house prices, derived from FHFA and Freddie Mac data. Also, in the default equation we include post-origination measures of house price changes as these changes affect home equity. All other explanatory variables are measured at the time of origination, as we seek to identify those factors knowable at the time of application for a mortgage that predict future default and can therefore inform policy changes and underwriting criteria.

Our complete sample includes 30,385 senior households, the majority (92.7 percent) of whom were counseled between 2008 and 2011. Of those counseled, 54.0 percent are linked to HUD data using confidential personal identifiers, indicating that they originated a HECM within two years of counseling. For our regression analysis, we limit our sample to 27,894 seniors with complete data on variables necessary to compute the amount of funds available through the HECM loan, including geographic location, home value and borrower age.[9] In the regression sample, 58.3 percent of the observations originate a HECM.

The primary outcome of interest in our analysis is whether or not a HECM borrower enters into technical default on their mortgage, as indicated by the lender making a corporate advance to cover property taxes or homeowner's insurance payments prior to the end of our period of observation in the data (June 30, 2014). While all corporate advance amounts and borrower repayments are reported in the HUD data, the dates of advances and payments are only known for a subset of borrowers. Therefore, in this analysis, we measure technical default with a dummy variable indicator, coded "1" if the lender has ever made a corporate advance on behalf of the borrower, regardless of date or borrower repayment. We also create a dummy variable designating a "severe-default" if the borrower experienced technical default and had an outstanding balance of $2,000 or more, net of any repayments, as of June 30, 2014. For the regression sample, of the 16,247 borrowers originating a HECM, 15.62 percent ever entered into technical default, with 6.4 percent in severe-default. This is similar to default rates in the population of HECM borrowers; according to the HECM 2014 actuarial report, the lifetime default rate for loans originated between 2006 and 2010 is around 15 percent,

[9] We also exclude borrowers in Puerto Rico and the Virgin Islands. For other variables with missing values, we preserve all observations and create missing data binary indicators that are reported on the summary tables and included in the regression analyses. For any given variable, approximately five percent of observations have missing values.

spiking at nearly 17 percent for loans originated in 2008 (Integrated Financial Engineering 2014).[10] To account for loan duration and loans that have terminated (through home sale, refinancing or foreclosure), we include a variable measuring the exposure time for each observation, from the date of origination to the date of termination or June 30, 2014.[11]

Tables 1-3 present descriptive statistics for our model variables. Summary statistics for the entire regression sample of counseled households (N=27,894) are included in the descriptive tables, in addition to sample means and proportions for those borrowers with a HECM mortgage (N=16,247), borrowers ever in technical default (N=2,537) and borrowers in severe technical default (N=1,047). Complete variable definitions are included in Appendix B. Our first set of explanatory variables includes those measuring the household's financial position at the time of counseling. These variables are included in models of all three outcomes. Monthly income is self-reported as the total of all retirement, wage and supplemental household income.[12] Non-housing assets include the self-reported total of money in checking, savings and retirements accounts, as well as the net value of property such as cars or boats.[13] All dollar amounts for variables are reported in tens of thousands.

We include a measure of liquidity from the credit report data, constructed as the amount of available revolving credit (Agarwal et al. 2007; Elul et al. 2010).[14] We also include debt to income calculated as the ratio of the revolving balance to annual income, and the installment balance to annual income. In all three equations, we include the amount of the monthly mortgage payment at the time of counseling. Because the HECM requires all existing mortgages to be paid off, the monthly payment amount indicates additional cash flow each month that potentially results from the HECM, likely influencing take-up, the withdraw amount, and default.

Of particular interest for this analysis is the ability of households to afford their property tax and insurance payments. We include a variable indicating property tax burden, defined as the expected annual property taxes calculated using county average property tax rates, multiplied by the property

[10] The IFE analysis (2011; 2012; 2013; 2014) does not include loans that have made any repayment in a 12 month period as being in default during that period, even if there is an outstanding balance.
[11] In our data, 12.73 percent of HECM loans terminated before June 30, 2014; only 10.35 percent terminated due to refinancing (1.3 percent of all HECM loans in our sample).
[12] In our data, we cap income at $30,000 per month (coding those with values in excess of $30,000 as missing).
[13] Non-housing assets are not reported at the time of counseling for about half of the observations in our sample. We thus include a dummy variable for no reported non-housing assets.
[14] In alternative specifications, we measure liquidity as the ratio of the outstanding revolving balance to the revolving credit limit and find it to be insignificant.

value at the time of counseling, divided by annual income.[15] Among those ever in technical default or in severe-default, the average property tax burden is very high at 10.7 percent and 13.2 percent, respectively. Data from the Survey of Consumer Finances indicate that only thirteen percent of senior homeowners spend more than 10 percent of their income on property taxes, and only six percent of non-senior homeowners have a greater than 10 percent property tax to income burden (Shan 2010). We also include a measure of the annual estimated dollar amount of property tax payments.

[Insert Table 1 Here]

The FICO credit score of the primary borrower at the time of counseling (measured in hundreds) provides an aggregate measure of credit risk, incorporating both payment histories (e.g. missed payments) and account liquidity (balances relative to account limits). We also include indicators for payment delinquencies at the time of counseling from the credit report file, including indicators for whether or not the existing mortgage was two months or more past due and an indicator for "foreclosure started", coded 1 if the borrower had a foreclosure in process when they completed counseling for the HECM. Aside from the mortgage, we include an indicator for any prior bankruptcy on the credit record in the 12 months prior to counseling. Finally, we include an indicator for whether or not the household had any tax liens or judgments on their credit file, potentially signaling a prior property tax delinquency.

Our second set of explanatory variables includes those measuring the management of HECM funds, and specifically, the proportion of funds withdrawn up-front. The initial withdrawal percent is calculated as the amount of funds withdrawn by the borrower in the first month (typically at closing) divided by the total amount of funds available. As reported in Table 2, the overall average initial withdrawal percentage is large, at 77 percent. The average initial withdrawal is more than 10 percentage points higher among those who ever-default or are in severe-default. We include the initial withdrawal percentage in the default equation, but treat it as endogenous.

We also include an array of variables that capture home equity at the time of counseling (or origination), measured differently depending on the outcome being modeled. In all three equations, we include a measure for the amount of funds available to the borrower from a HECM, which is the Initial Principal Limit (IPL). For the take-up equation, we estimate the maximum IPL that would be available to the household based on self-reported home value, the age of the youngest borrower and the interest

[15]To construct a measure for property tax burden, we merge in data at the county level on property tax rates from The Tax Foundation (2013). We use the three year average of property tax rates (2008-2010) and are missing property tax data for about six percent of the observations in our sample.

rate at the time of counseling.[16] For the withdrawal and default equations, we use the actual IPL based on the appraised home value and the terms of the HECM loan at origination.[17] In all three equations we also include a measure of the amount of home equity that is not available to the household through a HECM at counseling or origination, equaling the total value of the home (estimated or appraised) less the IPL (estimated or actual). We thus test whether the amount of untapped home equity influences the decisions to obtain a HECM, the amount withdrawn, and default. For the take-up and withdrawal equations, we include a measure of prior mortgage debt, equaling the sum of all outstanding mortgages divided by the IPL, as all prior mortgage debt must be paid off prior to obtaining a HECM. We cap this ratio at 1.0, as borrowers cannot withdraw an amount greater than the IPL and we do not expect a marginal increase in debt beyond the full amount of the IPL to differentially affect take-up.

Following the exclusion restrictions described in Section 4.2, each equation includes a set of variables unique to that equation, facilitating our identification strategy. For the take-up equation, we exploit an exogenous policy threshold for the maximum claim amount (MCA). The IPL is calculated based on the lesser of the appraised value of the home or the MCA limit. This limit has changed over time and by geography during our sample period. We construct a dummy indicator coded 1 if the appraised value of the home exceeds the MCA. We expect that households with home values in excess of the MCA limit are less likely to demand a HECM; however, after accounting for home equity, we do not expect this excess value amount to influence the withdrawal or default decisions. We also include an indicator for whether or not the household previously had a HELOC only in the take-up equation. We expect the presence of a HELOC may reflect a household's willingness to leverage home equity and thus obtain a HECM; however, we do not expect the presence of a prior HELOC to influence withdrawal or default decisions, as it must be paid off prior to obtaining the HECM and the outstanding balance is included in the measure of prior mortgage debt.

In the initial withdrawal equation, we include a policy variable indicating whether or not the counseling occurred after April 1, 2009, when the fixed rate, full-draw HECM product became available. We expect this policy variable to be strongly associated with higher initial withdrawals, as full draws at the time of origination are required for borrowers who elect to take a fixed rate loan. After April 1, 2009,

[16]This measure is based on the lesser of the self-reported home value at the time of counseling or the county specific FHA loan limit and the principal limit factor at the time of counseling adjusted for the borrower's age. For the principal limit, we use the greater of the PLF calculated using the average adjustable expected interest rate or using the average fixed interest rate as of the month of counseling.

[17]At the time of counseling, the appraised value of the home is not known. Arm's length appraisals are required by HUD after applying for a HECM. The mean absolute value of the difference between self-assessed house value and the appraised value is non-trivial, 10%.

we also include the spread between the average fixed and adjustable interest rates as of the month of HECM application. While typically one would expect adjustable rates to be lower than fixed rates, market conditions drove the fixed rate to be lower than the adjustable rate for a portion of the study period. We expect a negative spread to be associated with increased take-up of the fixed rate, full-draw product. The fixed rate policy change provides a clear identification strategy, as we expect the policy change to directly affect only the withdrawal amount—not the take-up of HECMs or technical default.[18]

Unique to the default equation are a series of time varying macro variables, measured as the cumulative annual change in the house price index from the time of closing. These variables allow us to test whether or not changes in house prices contribute to changes in default risk, as is commonly observed in the forward mortgage market.

[Insert Table 2 Here]

In all three equations, we include three macro-economic variables at the state level, derived from state-level FHFA and Freddie Mac data, measured in the year of counseling for a given household. They include the state's real GDP growth rate, a measure of house price volatility calculated based on the nine years prior to the survey year, and a measure of the deviation of the current real house price from the average real house price for the 1980 to 1999 period.[19] Following Haurin et al. (2014), we also include an interaction between state house price volatility and deviation.

All of our models include control variables for an array of demographic characteristics at the time of counseling, including race, ethnicity, marital status, gender, age of youngest senior household member and highest level of education completed (summarized in Table 3). With the exception of the time-varying house price indicators, all of the explanatory variables in our model are known at the time of origination. This limitation is appropriate for policy analysis because this is the set of information available to lenders (and HUD) when a HECM application is received.

[Insert Table 3 Here]

[18] The percentage of loans that were nearly full draws (90 percent or more of IPL) increased from 43 to 68 comparing the period before to that after the policy change.

[19] The selection of a nine year period to measure house price volatility is ad hoc. The number of observations of house prices must be sufficiently long to compute a measure of volatility, but not so long that it exceeds a reasonable period of recollection of price movements. We assume there is continuous updating of the volatility measure over time.

6. Results

6.1 Estimation Results-Default

Results are presented in Table 4. While we estimate the full series of equations for both outcomes ever-default and severe-default, the results of the selection and withdrawal equations are reported for the ever-default estimation only.[20] Column (1) reports the marginal effects for the probability of selection of a HECM, corresponding to Equation (1). We do not discuss the results of this equation in detail, as HECM take-up is not the focus of this analysis (see Moulton et al. 2014). Column (2) reports the coefficients for Equation (3), the OLS regression predicting the initial withdrawal amount. Column (3) reports the marginal effects for the probability of ever-default, conditioned on a household obtaining a HECM, corresponding to Equation (2).[21] Column (4) reports the marginal effects for the probability of severe-default, conditioned on a household obtaining a HECM and also corresponding to Equation (2).

We first consider variables that measure the cash-flow and liquidity of the household at the time of origination. Of note, the property tax amount is significantly associated with both types of default, and the property tax burden (amount/income) is predictive of severe-default. A $1,000 increase in the property tax amount is associated with a 1.03 percentage point increase in ever-default and a 0.54 percentage point increase in severe-default. Given that the base default rates are 15.6 percent for ever-default and 6.4 percent for severe-default; these effects are economically significant, corresponding to a 6.6 and 7.8 percent change in the probability of default, respectively. For severe-default, a 10 percent increase in the property tax burden is associated with a 0.77 percentage point increase in the default rate. This result confirms our expectation that the property tax burden can be a substantial constraint for HECM borrowers; those who are already burdened by property taxes at origination are more likely to experience difficulty managing future property tax payments.

Increased available revolving credit at the time of counseling, a measure of liquidity, is associated with reduced future default, where a $10,000 increase in available revolving credit is associated with a 0.9 percentage point decrease in the rate of ever-default and a 0.4 percentage point decrease in severe-default. Not having access to revolving credit significantly increases technical default

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[20]The results for the severe-default model's take-up and withdrawal equations are statistically and substantively similar to those for the ever-default model and are available from the authors upon request.

[21] The marginal effects for the default equation are the response of default to a one unit change in the explanatory variable, holding constant other explanatory variables, including the initial withdrawal. For example, while a change in income changes the withdrawal percentage, which affects the likelihood of default, we do not account for this in the reported marginal effects of income on default. Instead, we hold the initial withdrawal constant when reporting the marginal effect of income.

risk by 5.2 percentage points and severe-default risk by 2.7 percentage points, corresponding to 42.3 percent change in severe-default. This suggests that access to revolving credit may be important for managing property tax and insurance payments, extending findings about the role of credit liquidity for timely mortgage payments (e.g. Elul et al. 2010). The revolving debt to income ratio is negatively associated with ever-default, but does not reduce the probability of severe-default at 5% significance level, suggesting any impact is short-term. The installment debt ratio is not statistically significant. Monthly income at origination also appears to have a short term effect, where an increase in monthly income reduces the probability of ever entering technical default, but it does not significantly reduce the probability of severe-default. Non-housing assets are not significantly associated with default.

Indicators of past credit behaviors are strongly predictive of default in the forward mortgage market. Similarly, the credit score is statistically and economically associated with both types of technical default. A 100 point increase in credit score at the time of counseling is associated with a 7.8 percentage point decrease in the rate of ever-default, and a 3.8 percentage point decrease in severe-default which is a reduction in the rate of 59 percent. The elasticities with respect to ever-default and severe-default are 3.5 and 4.1, respectively. These values are similar to default elasticities for FICO scores on closed-end forward mortgages. Agarwal et al. (2006) find that a 5 percent decline in credit score results in a 15.9 increase in default probability for forward mortgage borrowers and a 17.2 percent increase in default for home equity lines of credit (closed end loans), corresponding to elasticities of 3.2 and 3.4 respectively. By contrast, they find that the elasticity with respect to default for open-ended HELOC borrowers is much lower, at 1.4.

Other indicators from credit report histories at the time of counseling are associated with increased default. Specifically, households who are past due two or more months on their forward mortgages at the time of counseling have ever-default rates that are 3.7 percentage points higher than other households, and severe-default rates that are 1.5 percentage points higher. Those with a prior tax liens or judgments on their credit histories have a 3.2 percentage point higher rate of ever-default, and a 1.9 percentage point higher rate of severe-default. Credit indicators for foreclosure or prior bankruptcy are not significantly associated with default.

A key focus of our analysis is evaluating the impact of the initial withdrawal on default. A higher upfront withdrawal from available HECM proceeds reduces the equity available in subsequent periods to cover planned or unplanned expenses. This is similar to HELOCs in the forward market, where a borrower’s choice of the proportion of available equity to extract upfront affects the amount remaining on the line of credit for future periods. Even after controlling for other risk factors and accounting for endogeneity, the proportion of funds taken as an initial withdrawal (e.g., within the first month after origination) is significantly associated with increased default. A 10 percentage point increase in the initial withdrawal is associated with a 2.3 percentage point increase in the rate of ever-default, and a 1.1 percentage point increase in the rate of severe-default. By contrast, the IPL is not significantly associated with default, suggesting that default risk is more directly tied to the timing of the withdrawal than the total funds available through the HECM.

In addition to the initial withdrawal, we also consider the impact of the total equity of a household, and anticipated changes in house prices over time. These indicators are consistent predictors of default in the forward market, particularly under conditions of negative equity. However, we expect these variables to exhibit less of an impact on default for HECM borrowers given that the federal insurance absorbs the cost of negative equity. For total equity, we include a measure for the house value at origination less the available funds from the HECM (appraised value less IPL). We expect an increase in untapped equity to be associated with a decrease in the default rate, as borrowers with increased total equity are more able to exercise the option to sell the home in response to a financial shock. However, we do not find a significant relationship between untapped equity or indicators of house price change with either type of default.

Household demographic characteristics affect default. Severe-default rates are greater for Hispanics (1.7 percentage points), blacks (1.8 percentage points), and for single male or female borrowers (3.5 and 1.7 percentage points). Older borrowers are less likely to default. Among the education measures, only having an advanced college degree is statistically significant, but it has a positive sign. Other demographic characteristics are not significantly associated with default. Our explanatory variables explain the spatial distribution of defaults relatively well, as only one of the state dummy variables are statistically different than zero in both regressions at 1%. As expected, a longer duration of exposure is also associated with increased default.

6.2 Estimation Results-Withdrawal

In our system of equations, we model the withdrawal amount as endogenous. This also allows us to identify factors associated with the initial withdrawal. Specifically, we explore evidence for consumption smoothing among constrained borrowers. In their analysis of HELOC borrowers, Agarwal et al. (2006a) find that HELOC borrowers with lower credit scores at origination withdraw less initially, arguing that this occurs because of the anticipation of future credit shocks. Our results suggest the opposite relationship between credit score and initial withdrawals for HECM borrowers. A 100 point increase in credit score is associated with a 2.7 percent decrease in the proportion of the initial withdrawal. Borrowers with lower credit scores may obtain HECMs to smooth consumption in the presence of a current shock, thus resulting in a higher initial withdrawal. By contrast, HELOC borrowers must be able to meet minimum credit underwriting criteria and demonstrate the ability to repay the loan; thus, they are more likely to obtain a HELOC when their credit and income are relatively stable and limit withdrawals up-front in expectation of future periods of constraint.

While we do not observe consumption smoothing behavior for credit constrained HECM borrowers, the property tax burden is a more applicable constraint for this population, as a major housing related expense for HECM borrowers is property taxes and insurance. Indeed, we find evidence that borrowers with a higher property tax burden withdraw less at origination. An increase in the property tax burden of 10 percent is associated with a 1.7 percentage point decrease in the initial withdrawal.

The identification of the withdrawal equation is based on the inclusion of a dummy variable for fixed rate HECMs, corresponding to the time period when fixed rate, full-draw loans were available. As expected, this variable is significantly associated with the initial withdrawal; loans made after this period have a 4.8 percentage point increase in the initial withdrawal percentage. However, the interest rate spread after the fixed rate period is not significantly associated with higher withdrawals. As expected, an increase in the mortgage debt as a percentage of the initial principal limit is significantly associated with a higher initial withdrawal, as borrowers must pay-off existing mortgage debt from available funds or in cash upon origination of the HECM. A higher amount of untapped equity (appraised value-IPL) is associated with a reduced initial HECM withdraw; specifically, a $100,000 increase in untapped equity at origination is associated with a 3.1 percentage point decrease in the initial withdrawal proportion. The amount of the initial principal limit is not significantly associated with the initial withdrawal.

6.3 Correlation of Errors among Equations

Finally, we consider the correlations of errors (ρ) between the three equations, representing unobserved characteristics associated with HECM take-up, default and the initial withdrawal.[22] For both ever-default and severe-default, the correlation of errors between the take-up and default equations is statistically significant and negative (-0.38 and -0.52). Perhaps this reflects unmeasured financial

[22]Accounting for selection and the endogeneity of the initial withdrawal changes the key estimated coefficients by about 10 percent, compared to estimates resulting from a simple probit default model. Compared to estimates produced from HUD data alone, our analysis includes a much greater set of explanatory variables (including credit attributes), many of which are statistically significant with large effects.

planning behaviors that increase the likelihood of obtaining a HECM and reduce default. This suggests that there is not unobserved adverse selection among those counseled that contributes to default; in fact, unobserved selection is advantageous for default outcomes. The correlation of errors between the take-up and withdrawal equations for both models is statistically significant and positive (0.32), perhaps indicative of an unobserved need for cash that drives a borrower to obtain a HECM and is also associated with a higher initial withdrawal. Finally, the correlation of errors between the withdrawal and default equations is small and not statistically significant.

[Insert Table 4 Here]

6.4 Alternative Specifications and Robustness Checks

The findings presented above are robust to a variety of alternative specifications. While our empirical specification accounts for selection into a HECM by modeling HECM take-up, the generalizability of our findings are limited to those who seek counseling for a reverse mortgage. We expect that households who seek counseling may differ from households in the general population of seniors. In an alternative specification, we merge our sample data with Health and Retirement Study (HRS) data, this being a sample of the general population of senior households. We limit the years of the data in our CredAbility sample to households counseled in 2009-2011, corresponding to the 2010 wave of the HRS. Next, we re-estimate the system of equations but use the full HRS and CredAbility samples in equation (1), following the strategy described in Moulton et al. (2014). Our set of explanatory variables included in (1) is much more limited, as the HRS data lacks information on property tax payment burden and all credit report indicators. However, key variables measuring income, non-housing assets, house value and debt, and mortgage delinquency are included in the HRS survey data and are used for this analysis. Our full set of explanatory variables is still included in the default and withdrawal equations. We find that our primary variables are robust to the alternative specification. Specifically, after accounting for selection into a HECM from the general population, property tax amount, credit risk indicators and the initial withdrawal remain significantly associated with both types of technical default, with economically similar effects.

Data constraints limit our measure for technical default to be a binary indicator. Another indicator of default severity often analyzed for forward mortgages is whether or not a default has cured (e.g. Ambrose and Capone 1998). While we do not have the date of the corporate advance for more than half of our observations, we do have an indicator for whether or not the borrower "cured" the default by repaying the amount of the corporate advance. In our sample data, 28.7 percent of households who had ever been in technical default (ever-default) had cured as of June 30, 2014. We reestimated the system of equations, recoding technical default in equation (2) as borrowers who experienced default and had not yet cured (N=1,808). We again find that our results are statistically and economically similar, where higher property taxes, a lower credit score, and higher initial withdrawal are significantly associated with technical defaults that have not cured. The magnitude of most of the coefficients fall in between the ever-default and severe-default coefficients, as would be expected based on the definitions of the default variables.

We also explore additional evidence for consumption smoothing behaviors associated with the initial withdrawal amount. A constraint that may be applicable to HECM borrowers is poor health and anticipated higher medical expenses associated with poor health. In their theoretical model of HECM demand, Nakajima and Telyukova (2013) model poor health as a primary motivating factor leading a household to take out a HECM, in expectation of future health related expenses. Thus, we might expect households in poor health at the time of origination to withdraw less up front to smooth future consumption. While we do not have a measure for health in our full sample population, we do have an indicator of health status (poor, fair, or good) for households counseled after October, 2010. Using this sub-sample, we analyze the relationship between health status and the initial withdrawal. We do not find evidence that poor health at the time of counseling is significantly correlated with lower (or higher) initial withdrawal amounts.

We estimate our models with a variety of alternative specifications for our explanatory variables, checking for nonlinear relationships and interactions. For example, the IFE (2013) analysis of technical default in the HECM program includes a nonlinear term for the initial withdrawal amount, specifically including a spline at 90 percent. Their analysis finds that the slope for default risk decreases significantly for draws above 90 percent. To check for nonlinearities in the initial withdrawal in our analysis, we divide the initial withdrawal amount into four equal groups corresponding to the distribution, allowing the slope to differ for each group, at less than 60 percent, 60 to 90 percent, 90 to 95 percent and greater than 95 percent. We find no statistically significant differences between these groups, suggesting that the linear specification employed in our primary model is appropriate. Similarly, we test for nonlinearities on credit score, dividing it into buckets. We find that the coefficients for the credit score categories decrease monotonically, suggesting that the linear specification for credit score is appropriate.

We estimate a series of interactions between model variables, including interactions between credit score and the initial withdrawal amount, and liquidity and the initial withdrawal amount, based on the expectation that there could be a layering effect of risk characteristics where higher initial withdrawals present greater default risk for illiquid households or households with poor credit management, similar to risk layering with LTV in the forward mortgage literature (Mayer, Pence and Sherlund 2009). In the ever-default model, we find a statistically significant negative interaction between credit score and withdrawal, where an increase in the initial withdrawal has less of an impact on default as credit score increases. However, the credit score interaction is not statistically significant for severe-default, and the liquidity interaction is not statistically significant for either default outcome.

Finally, we test for an interaction between the fixed rate policy dummy and the initial withdrawal amount. It is possible that households making large up-front withdrawals after the fixed rate policy change were substantively different than households making large up-front withdrawals prior to the policy change. HECM borrowers who may have preferred a lower initial withdrawal (and are thus less risky) are forced to withdraw all proceeds up-front if they select a fixed rate HECM after the policy change. Thus, the probability of default associated with higher withdrawals may be lower after the fixed rate policy. We find some evidence of this for ever-default, where the interaction between the initial withdrawal amount and the fixed rate policy indicator is negative and statistically significant. However, the magnitude of this effect is small, and not statistically significant for severe-default. In addition to including an interaction term for the policy dummy and initial withdrawal in the base model, we re-estimate the entire system of equations for households counseled prior to and after the policy change to check to see if other model variables operate differently on default in the two periods. We find that our results are stable between the two periods, with coefficients that are identical or nearly identical for our key variables including credit score, property tax amount and the initial withdrawal.

6.3 Simulation Results

As a final exercise, we use the estimates from the regression model to simulate the effect of imposing various underwriting criteria on the predicted take-up of HECMs and the probability of ever-default or severe-default as of June 30, 2014, for HUD's HECM portfolio from 2008 to 2011. Using the estimated regression coefficients, we explore changes in take-up and default probabilities based on imposing withdrawal restrictions at the time of origination and certain credit risk thresholds. Unlike the marginal effects presented earlier, our simulations allow for feedback within the system of equations. For example, the initial withdrawal is treated as endogenous in the take-up and default equations, and thus a forced change to the initial withdrawal affects the simulated probability that a borrower previously taking out a HECM will still elect to take out a HECM. We expect there to be no impact of the policy change on households who did not previously elect to take-out a HECM, as it is unlikely that the added restrictions would induce households to take a HECM.

Our simulation results are presented in Tables 5 and 6, where Table 5 simulations are based on the model for ever-default and Table 6 simulations are based on the model for severe-default. For each proposed underwriting criteria, we report the predicted change in the HECM take-up rate, and predicted change in technical default rates.[23] The predictions of average probabilities are based on our sample of HECM households, weighted to be representative of the full HECM population of originations by census division and year.[24]

[Insert Tables 5 and 6 Here]

First, we impose the new initial withdraw restrictions for all HECM households in our sample. Following HUD's guidelines, we restrict households without existing mortgage debt at the time of origination to the lesser of a 60 percent withdrawal of IPL or the actual amount drawn at origination.[25] This simulation assumes that if the observed initial withdrawal percentage for a household in our data exceeds the policy limit, the household withdraws the policy limit. Based on our models, we estimate that the initial withdrawal restriction would result in 17.8 percent reduction in the probability of ever-default (Table 5), and a 20 percent reduction in the probability of severe-default (Table 6). We estimate that the withdrawal limit would have decreased HECM volume by about 7.5 percent (Table 6). Based on the confidence intervals, the reductions in take-up and default are statistically significant at the 5 percent level.

Next, we simulate the impact of specific credit risk thresholds on the probability of HECM take-up and default. We begin by imposing credit score thresholds a t FICO scores of 500 and 580, and alternatively impose a threshold for "bad credit," defined as occurring when a borrower has any credit history of a delinquent mortgage, foreclosure, tax lien or judgment, delinquent installment debt or delinquent revolving debt. First, we treat the credit risk thresholds as a hard cut-off, dropping households from the HECM program that fail the specific thresholds. Second, we impose a life expectancy set-aside (LESA) requirement for borrowers failing the credit risk thresholds. If a borrower

[23] We report each predicted probability as a point estimate. The 95% confidence intervals are bootstrapped using 100 replications and assume a normal-approximation confidence interval.

[24] The results of the weighted and unweighted simulations are substantively similar. Unweighted simulations are available from the authors.

[25] Households with mortgages are limited to the initial withdrawal percentage necessary to pay-off their existing mortgages, an up-front mortgage insurance premium of 2.5 percent if the mortgage is over 60 percent of IPL and 0.5 percent otherwise, $3,400 in closing costs plus (1) any additional actual initial withdrawal amount, up to 60 percent of IPL (for those whose mortgages are less than 60 percent of IPL), or (2) up to 10 percent additional IPL (for those whose mortgages are greater than 60 percent of IPL).

fails the credit risk threshold, but can afford the LESA plus all other mandatory obligations, we retain them in the HECM sample and set their default probability to zero, given that they have set aside funds to cover their property taxes and insurance for their expected lifetime. If the borrower fails the credit risk threshold but cannot afford the LESA, we exclude them from the HECM program. Finally, we combine the specific credit risk threshold, LESA requirement and initial withdrawal restrictions to simulate the maximum policy impact on HECM take-up and default.

In order to identify which borrowers can afford the LESA, we estimate LESA for each HECM borrower in our sample. To do this, we use the formula for LESAs provided by HUD (Mortgagee Letter 2013-27):

$$\text{LESA} = (\text{PC} \div 12) \times \{(1 + c)^{m+1} - (1 + c)\} \div \{c \times (1 + c)^{m}\}.$$

In the above formula, PC is equal to the annual property charges for taxes and homeowner's insurance. To estimate total property charges for HECM borrowers in our sample, we use our county level estimate of property taxes plus an annual homeowner's insurance rate of 3.5 percent multiplied by the home value/1,000.[26] Following HUD's guidelines, we multiply the estimated annual property tax and insurance amount by 1.2 to get the total annual property charge; this represents their adjustment factor for future tax increases.[27] For the monthly compounding rate, c, we divide the sum of the HECM expected rate and the annual mortgage insurance premium of 1.25 percent by 12. Finally, m is the life expectancy for a given borrower, in months, as derived from the life expectancy table provided in the mortgagee letter. We consider a household is able to "afford a LESA" if the amount of the LESA is less than or equal to the initial principal limit on the HECM minus any outstanding mortgage debt, closing costs and up-front mortgage insurance premium (MIP) at the time of origination.

For households who fail the threshold but can afford LESA, we assume that the IPL will be reduced by the amount of the LESA while the amount of untapped equity will increase, which may affect a household's decision to obtain a HECM. The estimated coefficients in Table 4 show that a decrease in IPL and an increase in untapped equity are associated with a decrease in HECM take-up.

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[26]Our rate of 3.5 for homeowner's insurance is derived from a general rule of thumb published in an online consumer education resource from the Federal Reserve: http://www.federalreserve.gov/pubs/settlement/. This does not account for regional variations in insurance rates (e.g., flood insurance required in particular areas), but provides a rough estimate of average insurance costs.

[27]Based on our assumptions about property tax and insurance rates, the average annual property charge for a borrower in our sample is $3,218*1.2 = $3,861. In comparison, total average self-reported property charges (homeowner's insurance and property taxes) for households in our sample is $3,814.

In our sample of HECM borrowers, we estimate that imposing a hard credit score threshold at a FICO of 500 would reduce the predicted ever-default rate by 9.8 percent (Table 5), and reduce the probability of severe-default by 12.9 percent (Table 6), with a slight reduction in predicted HECM volume of about 3 percent. If a LESA was required rather than a hard cut-off at a credit score of 500, we predict that the ever-default and severe-default rates would decline by 12.0 and 14.3 percent, respectively. A credit score threshold of 580 has a much greater expected impact on the default rate, with a statistically significant reduction of ever-default of 29.8 percent and severe-default of 35.7 percent; however, this also corresponds to a statistically significant reduction in HECM volume of about 12 percent. However, if a LESA requirement was imposed rather than a hard cut-off, the threshold of 580 would reduce the predicted ever-default rate by 37.0 percent and the severe-default rate by 41.4 percent, with a smaller reduction in HECM volume of about 4 percent.

Alternatively, credit risk thresholds could be applied based on derogatory credit histories instead of credit scores. In our simulations, imposing a hard cut-off for indicators of bad credit has a very similar impact on the predicted default rate as a credit score cut-off at 580. Finally, imposing the initial withdrawal restrictions on top of the credit risk thresholds has an additional impact on reducing the predicted default rate for all thresholds, but such restrictions are also associated with a further reduction in HECM volume.

It is important to caution that our simulations assume that borrowers will continue to withdraw at the same rate over the lifetime of the HECM that they did prior to the policy change. If borrowers withdraw at a higher rate after the first year restriction, the rate of default may be reduced in the first year but increase when the limit expires. Thus, our estimates should be viewed as the maximum estimated effect of the initial withdrawal restriction on both take-up and default; the actual impact is likely somewhere between zero (if borrowers are completely strategic and simply postpone withdrawals) and our estimated impact.

7. Conclusions

Federally insured HECMs have the potential to play an important role in enabling financial security for senior homeowners. However, the more than 12 percent default rate on property taxes and homeowners insurance among HECM borrowers raises significant concerns. A variety of policy responses have been put into effect, including establishing risk-based underwriting guidelines for the first time in the program's history.

Given the lack of prior data and empirical analysis, the first objective of this study is to identify factors contributing to default risk for reverse mortgage borrowers, extending the literatures on reverse mortgages and mortgage default. We accomplish this objective using a comprehensive dataset of households who sought counseling for a reverse mortgage, linked to loan level data indicating whether or not the household obtained a reverse mortgage and characteristics of the reverse mortgage, including the initial withdrawal percentage and whether or not they were ever in technical default on their loan. We expect that unobserved characteristics associated with a borrower's decision to take out a HECM may also be associated with technical default. We therefore use a bivariate probit model with sample selection to analyze a household's decision whether to obtain a HECM, and conditional on origination, whether to default.

Building from the literature on leverage and default in the forward mortgage market, a key explanatory variable in our model is the percentage of HECM funds withdrawn during the first month. As expected, the initial withdrawal is an important factor predicting default. An increase in the initial withdrawal of 10 percentage points is associated with a 14.6 percent increase in the probability of ever entering technical default, and a 17.0 percent increase in the probability of severe default. We also find evidence in line with consumption smoothing behaviors. HECM borrowers with higher property tax burdens as a percentage of income have lower initial withdrawals. Similar to research on initial withdrawals on home equity lines of credit, HECM borrowers who expect higher constraints (property tax burden) in future periods may withdraw less up-front, resulting in a larger line of credit from which to maintain consumption in future periods (Agarwal et al. 2006a).

We find statistically significant relationships between default and risk characteristics including credit score, liquidity, delinquency on mortgage debt, and prior tax liens. Having a delinquent mortgage or prior tax lien raises the probability of severe default by 23.4 and 29.7 percent, respectively. The elasticity of default with respect to the FICO score is large, -3.5 and -4.1 for ever- and severe-default. Our default rates with respect to credit scores are similar to those for closed ended first mortgages and home equity loans, but larger than that observed for HELOCs (Agarwal et al. 2006b). Household liquidity is also important; the probability of severe default is reduced by 42.2 percent if a household has access to revolving credit and it also is reduced the greater is the percentage of unused revolving credit. These results are stable for the period before and after the fixed rate policy change.

A second objective of our analysis is to identify the impact of various policy changes. The simulation estimates take into account the feedback between our system of equations, allowing for the identification of the effect of a particular change on both the probability of default and participation in the HECM program. Limits on the initial withdrawal reduce the probability of default by as much as 20 percent; however, such limits also significantly reduce the take-up of HECMs. Had such limits been in place for loans in our sample, we predict that HECM volume would have declined by 7.5 percent. A greater reduction in the default rate with less of an impact on HECM volume can be achieved by requiring higher risk borrowers to set aside funds at the time of origination for future property taxes and homeowner's insurance. For higher risk borrowers, the LESA policy enacts an institutional mechanism to reduce default, similar to an escrow required for forward mortgage borrowers.

Finally, it is important to consider the broader implications of tax and insurance default for the HECM program. Similar to forward mortgages, technical default in the HECM program accelerates the prepayment of the mortgage, requiring the servicer to call the loan due and payable if the default cannot be cured within a specified period of time. The primary risk associated with prepayment in the HECM program is crossover risk, where the balance on the loan exceeds the home value at the time of termination. The federal government acting through FHA's MMI fund bears this risk. Borrowers defaulting on taxes and insurance are not necessarily underwater on their HECMs, as is often the case in the forward mortgage market. To the extent that there is still equity left on the subject property, borrowers defaulting on taxes and insurance may not require claims against the MMI fund. However, tax and insurance defaults may be indicative of underlying financial problems that are associated with disinvestment in the subject property. Such disinvestment may reduce the value of the home and increase crossover risk among defaulted HECMs. Further, house price dynamics in the macro-economy impact crossover risk. In the post 2006 period when nominal house prices fell after origination, default and foreclosure were costly to the MMI fund. In the future, if house prices return to grow at the rate of inflation, these costs will be less. Unpacking the relationships between technical defaults, house prices and crossover risk is beyond the scope of this study, but is an important topic for future research.

The viability of the HECM program depends not only on the fiscal solvency of the MMI fund, but also on the perceived public value of the program. If large numbers of senior homeowners with HECMs are being foreclosed upon for failure to pay property taxes and insurance, there is significant risk to the program, regardless of crossover risk. The fact that seniors in tax and insurance default may have equity remaining in the property may exacerbate public concerns about the program's purpose and policy effectiveness. Foreclosing on senior homeowners for a relatively small tax bill in comparison to the amount of equity in their properties has been perceived negatively by senior advocacy groups and the general public. However, putting in place underwriting requirements to stem future defaults that overly restrict access to the product could also be perceived as antithetical to the public mission of the HECM program. Addressing the tax and insurance default problem without compromising the mission to serve the needs of senior homeowners is thus a significant issue for the policy viability of the HECM program. While our analysis does not address broader implications related to the fiscal solvency of the program and the MMI fund, it does offer insights that can inform policy design-- and market innovations—to address the viability of the HECM program over the longer term.

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Table 1, Summary Statistics for Household Financial Characteristics

	Counseled (N=27,894)		HECM (N=16,247)		Ever Default (N=2,537)		Severe Default (N=1,047)	
	mean	sd	mean	sd	mean	sd	mean	sd
Monthly income	0.220	(0.18)	0.219	(0.17)	0.175	(0.14)	0.176	(0.14)
Monthly income, missing	0.054	(0.23)	0.064	(0.24)	0.088	(0.28)	0.103	(0.30)
Non-housing assets	4.284	(18.04)	4.196	(17.34)	2.751	(15.01)	2.904	(15.42)
Non-housing assets are zero	0.507	(0.50)	0.511	(0.50)	0.611	(0.49)	0.611	(0.49)
Property tax amount	0.192	(0.22)	0.198	(0.19)	0.185	(0.18)	0.231	(0.23)
Tax burden, property taxes/income	0.092	(0.10)	0.096	(0.10)	0.107	(0.10)	0.132	(0.12)
Tax burden, missing	0.059	(0.24)	0.067	(0.25)	0.092	(0.29)	0.107	(0.31)
FICO credit score (100s)	6.779	(1.03)	6.932	(0.99)	6.098	(0.93)	6.018	(0.90)
FICO credit score, missing	0.065	(0.25)	0.063	(0.24)	0.084	(0.28)	0.090	(0.29)
Revolving balance/income	0.230	(0.45)	0.251	(0.48)	0.192	(0.43)	0.193	(0.45)
Installment balance/income	0.233	(0.49)	0.220	(0.48)	0.277	(0.56)	0.254	(0.55)
Monthly Mortgage Payment	0.050	(0.07)	0.047	(0.07)	0.047	(0.07)	0.054	(0.08)
Foreclosure started	0.021	(0.14)	0.011	(0.10)	0.030	(0.17)	0.034	(0.18)
Bankruptcy in last 12 months	0.011	(0.11)	0.007	(0.08)	0.013	(0.11)	0.011	(0.10)
Available revolving credit	2.271	(3.76)	2.576	(3.83)	0.922	(2.05)	0.941	(2.18)
No revolving credit	0.148	(0.35)	0.112	(0.32)	0.238	(0.43)	0.251	(0.43)
Mortgage past due, 2+ months	0.061	(0.24)	0.039	(0.19)	0.104	(0.30)	0.116	(0.32)
Tax lien or judgment	0.104	(0.31)	0.080	(0.27)	0.162	(0.37)	0.186	(0.39)
Missing credit report data	0.073	(0.26)	0.089	(0.28)	0.117	(0.32)	0.118	(0.32)

Note: Summary statistics are reported excluding missing observations. For the regression analysis, the missing dummy indicator is included for each respective variable (or set of variables for missing credit report data) and missing observations are coded as "0".

All dollar amounts are in ten-thousands.

Table 2, Summary Statistics for Mortgage Characteristics

	Counseled (N=27,894)		HECM (N=16,247)		Ever Default (N=2,537)		Severe Default (N=1,047)	
-	mean	sd	mean	sd	mean	sd	mean	sd
Initial withdrawal %			0.769	(0.29)	0.879	(0.17)	0.877	(0.17)
HECM Take-Up Equation								
Estimated IPL	14.444	(9.36)	15.096	(9.28)	13.489	(8.23)	15.481	(8.70)
Estimated home value-IPL	8.839	(11.34)	9.052	(10.55)	7.589	(8.29)	9.079	(9.88)
Home value exceeds MCA	0.089	(0.28)	0.102	(0.30)	0.093	(0.29)	0.131	(0.34)
Mortgage debt/Estimated IPL	0.400	(0.37)	0.366	(0.34)	0.416	(0.34)	0.422	(0.33)
HELOC	0.133	(0.34)	0.142	(0.35)	0.094	(0.29)	0.101	(0.30)
Initial Withdrawal & Default Equations								
Actual IPL			14.031	(8.82)	12.541	(7.98)	14.450	(8.51)
Appraised value-IPL			8.310	(8.97)	6.785	(6.78)	8.119	(8.30)
Initial Withdrawal Equation								
Mortgage debt/Actual IPL			0.386	(0.35)	0.440	(0.35)	0.447	(0.34)
Fixed rate policy indicator			0.736	(0.44)	0.591	(0.49)	0.556	(0.50)
Fixed rate policy*spread			-0.068	(0.35)	-0.078	(0.33)	-0.100	(0.33)
Technical Default Equation								
HPI Δ, 1 year			-0.062	(0.05)	-0.074	(0.06)	-0.080	(0.06)
HPI Δ, 2 year			-0.087	(0.10)	-0.117	(0.11)	-0.129	(0.11)
HPI Δ, 3 year			-0.083	(0.15)	-0.131	(0.15)	-0.147	(0.15)
HPI Δ, 4 year			-0.090	(0.14)	-0.137	(0.15)	-0.150	(0.15)
HPI Δ, 5 year			-0.075	(0.13)	-0.117	(0.15)	-0.127	(0.15)
Exposure days (hundreds)			14.442	(5.25)	16.470	(5.22)	16.932	(5.01)
All Equations								
State house price deviation	0.218	(0.22)	0.247	(0.24)	0.281	(0.26)	0.335	(0.27)
State house price volatility	19.496	(13.16)	19.961	(13.23)	21.273	(14.49)	23.845	(14.29)
State house price deviation*volatility	5.530	(7.65)	6.382	(8.62)	8.165	(10.27)	10.127	(11.03)
State GDP growth	0.006	(0.03)	0.006	(0.03)	-0.001	(0.03)	-0.003	(0.03)

Note: All dollar amounts are in ten-thousands.

Table 3, Summary Statistics for Demographic Characteristics

	Counseled (N=27,894)		HECM (N=16,247)		Ever Default (N=2,537)		Severe Default (N=1,047)	
	mean	sd	mean	sd	mean	Sd	mean	sd
Hispanic	0.098	(0.30)	0.088	(0.28)	0.144	(0.35)	0.165	(0.37)
Hispanic, missing	0.021	(0.14)	0.027	(0.16)	0.034	(0.18)	0.042	(0.20)
Race, white	0.643	(0.48)	0.685	(0.46)	0.518	(0.50)	0.516	(0.50)
Race, black	0.168	(0.37)	0.128	(0.33)	0.231	(0.42)	0.217	(0.41)
Race, Asian	0.009	(0.10)	0.009	(0.09)	0.007	(0.08)	0.008	(0.09)
Race, missing	0.067	(0.25)	0.072	(0.26)	0.092	(0.29)	0.098	(0.30)
First language, not English	0.059	(0.23)	0.050	(0.22)	0.096	(0.29)	0.113	(0.32)
Unmarried Male	0.162	(0.37)	0.158	(0.36)	0.191	(0.39)	0.224	(0.42)
Unmarried Female	0.362	(0.48)	0.393	(0.49)	0.443	(0.50)	0.431	(0.50)
Age, youngest household member	71.674	(8.11)	72.198	(7.96)	71.751	(8.04)	71.952	(8.44)
Education, bachelors degree	0.111	(0.31)	0.111	(0.31)	0.083	(0.28)	0.089	(0.28)
Education, high school diploma	0.323	(0.47)	0.307	(0.46)	0.311	(0.46)	0.289	(0.45)
Education, missing	0.186	(0.39)	0.217	(0.41)	0.277	(0.45)	0.310	(0.46)
Education, advanced degree	0.049	(0.22)	0.046	(0.21)	0.035	(0.19)	0.045	(0.21)
Education, some college	0.201	(0.40)	0.199	(0.40)	0.160	(0.37)	0.145	(0.35)

Table 4, Probit Results with Sample Selection and Endogenous Withdrawal

	HECM		Withdrawal		Ever Default		Severe Default[1]	
Monthly income	0.359	***	0.102	***	-0.199	***	0.018	
	(0.046)		(0.034)		(0.041)		(0.039)	
Monthly income (squared)	-0.202	***	-0.041	*	0.095	***	-0.059	
	(0.034)		(0.025)		(0.026)		(0.038)	
Monthly income, missing	0.165	***	0.067	**	-0.020		0.019	
	(0.042)		(0.029)		(0.040)		(0.032)	
Non-housing assets	-4.2E-04	**	2E-04	*	2.5E-04		0.5E-04	
	(1.7E-04)		(1E-04)		(1.6E-04)		(1.2E-04)	
Non-housing assets are zero	-0.002		8E-04		0.008		-0.002	
	(0.006)		(0.004)		(0.006)		(0.004)	
Property tax amount	-0.042	*	-0.006		0.103	***	0.054	***
	(0.024)		(0.023)		(0.023)		(0.014)	
Property taxes/income	0.090	*	-0.169	***	0.009		0.077	***
	(0.048)		(0.037)		(0.041)		(0.026)	
Property taxes/income, missing	-0.081	**	-0.054	*	-0.010		-0.002	
	(0.041)		(0.028)		(0.040)		(0.032)	
FICO credit score	0.048	***	-0.027	***	-0.078	***	-0.038	***
	(0.004)		(0.003)		(0.003)		(0.002)	
FICO credit score, Missing	0.282	***	-0.186	***	-0.524	***	-0.255	***
	(0.027)		(0.019)		(0.024)		(0.017)	
Revolving balance/income	0.047	***	0.040	***	-0.019	***	-0.008	*
	(0.007)		(0.004)		(0.006)		(0.005)	
Installment balance/income	-0.001		0.013	***	0.002		-0.004	
	(0.006)		(0.004)		(0.005)		(0.004)	
Mortgage and HELOC monthly payments	-0.109	**	0.264	***	-0.090		-0.030	
	(0.052)		(0.034)		(0.056)		(0.038)	
Foreclosure started	-0.078	***	-0.022		0.026		-0.002	
	(0.024)		(0.018)		(0.022)		(0.014)	
Bankruptcy in last 12 months	-0.083	***	-0.036	**	-0.001		-0.007	
	(0.027)		(0.018)		(0.027)		(0.019)	
Available revolving credit	-0.001		-0.003	***	-0.009	***	-0.004	***
	(0.001)		(7E-04)		(0.001)		(0.001)	
No revolving credit	-0.041	***	0.006		0.052	***	0.027	***
	(0.009)		(0.007)		(0.008)		(0.005)	
Mortgage past due, 2+ months	-0.040	***	-0.043	***	0.037	***	0.015	*
	(0.015)		(0.008)		(0.013)		(0.008)	
Tax lien or judgment	-0.033	***	0.016	**	0.032	***	0.019	***
	(0.009)		(0.006)		(0.008)		(0.005)	
Missing credit report data	-0.058	***	0.033	**	0.014		0.007	
	(0.017)		(0.014)		(0.016)		(0.011)	

Table 4, (cont.)

	HECM		Withdrawal		Ever Default		Severe Default[1]	
Initial withdrawal %					0.227	***	0.109	***
					(0.031)		(0.024)	
Estimated IPL	0.004	***						
	(0.001)							
Estimated home value- IPL	-0.003	***						
	(4.9E-04)							
Home value exceeds MCA	0.024	*						
	(0.014)							
Mortgage debt/Estimated IPL	-0.100	***						
	(0.009)							
HELOC	0.018	**						
	(0.009)							
Actual IPL			0.000		-0.001		3.5E-04	
			(5E-04)		(0.001)		(3.7E-04)	
Appraised value-IPL			-0.003	***	-4.7E-04		0.4E-04	
			(4E-04)		(5.7E-04)		(3.6E-04)	
Mortgage debt/Actual IPL			0.308	***				
			(0.006)					
Fixed rate policy indicator			0.048	***				
			(0.011)					
Fixed rate policy*spread			-0.008					
			(0.007)					
Exposure days					0.018	***	0.018	***
					(0.004)		(0.003)	
Exposure days (squared)					-1.3E-04		-1.8E-04	*
					(1.4E-04)		(1.0E-04)	
HPI Δ, 1 year					0.349		0.080	
					(0.256)		(0.186)	
HPI Δ, 2 year					-0.271		-0.062	
					(0.215)		(0.158)	
HPI Δ, 3 year					0.082		-0.041	
					(0.115)		(0.085)	
HPI Δ, 4 year					-0.046		0.006	
					(0.086)		(0.062)	
HPI Δ, 5 year					-0.015		-0.040	
					(0.105)		(0.073)	

Table 4, (cont.)

	HECM		Withdrawal		Ever Default		Severe Default[1]	
State house price deviation	0.048		-0.215	***	-0.056		-0.001	
	(0.078)		(0.048)		(0.070)		(0.051)	
State house price volatility	-0.003	***	-3E-04		0.002	***	0.002	***
	(0.001)		(4E-04)		(0.001)		(0.001)	
State house price deviation*volatility	0.002		0.004	***	-2.5E-04		-0.002	
	(0.002)		(0.001)		(0.002)		0.001	
State GDP growth	0.068		-0.047		-0.301	**	0.117	
	(0.245)		(0.114)		(0.147)		(0.102)	
Hispanic, missing	0.152	***	0.011		0.030	*	0.026	**
	(0.024)		(0.015)		(0.018)		(0.011)	
Hispanic	-0.009		0.023	**	0.023	*	0.017	**
	(0.014)		(0.010)		(0.013)		(0.008)	
Race, missing	0.047	***	-0.004		-0.019		-0.010	
	(0.017)		(0.011)		(0.014)		(0.009)	
Race, white	0.055	***	0.001		-0.005		0.006	
	(0.011)		(0.008)		(0.010)		(0.007)	
Race, black	-0.063	***	0.041	***	.0.031	***	0.018	**
	(0.013)		(0.009)		(0.011)		(0.008)	
Race, Asian	-0.019		0.014		0.010		0.015	
	(0.030)		(0.022)		(0.028)		(0.020)	
Unmarried male	0.064	***	0.032	***	0.040	***	0.035	***
	(0.008)		(0.006)		(0.008)		(0.005)	
Unmarried female	0.126	***	0.010	*	0.021	***	0.017	***
	(0.007)		(0.005)		(0.006)		(0.005)	
Age, youngest household member	0.020	***	0.008	**	-0.008	**	-0.010	***
	(0.004)		(0.004)		(0.004)		(0.003)	
Age, squared	-1.4E-04	***	-1E-04	***	0.6E-04	**	0.7E-04	***
	(0.3E-04)		(0.000)		(0.3E-04)		(0.2E-04)	
First language, not English	-0.041	**	0.059	***	-0.002		-0.002	
	(0.018)		(0.012)		(0.016)		(0.011)	
Education, bachelors degree	-0.3E-04		-0.034	***	0.015		0.011	
	(0.011)		(0.009)		(0.011)		(0.008)	
Education, high school	-0.003		-0.009		0.018	**	0.008	
	(0.009)		(0.007)		(0.008)		(0.006)	
Education, missing	0.007		-0.008		0.021	*	0.019	**
	(0.013)		(0.009)		(0.012)		(0.008)	
Education, advanced degree	-0.037	**	-0.037	***	0.034	**	0.024	**
	(0.015)		(0.011)		(0.015)		(0.010)	
Education, some college	0.004		-0.012		0.011		0.006	
	(0.010)		(0.007)		(0.009)		(0.007)	
State Fixed Effects	Y		Y		Y		Y	
Year Fixed Effects	Y		Y		Y		Y	
Constant	-3.109	***	0.577	***	1.848	**	2.082	**

*** p<0.01, ** p<0.05, * p<0.1

[1]Severe default system of equations estimated but not shown
Probit estimates reported as conditional marginal effects (default) and selection marginal effects (HECM). Robust standard errors in parentheses.

Table 5: Policy Simulations: Predicted Default Probability Conditional on HECM, Weighted, Ever-Default

	Predicted HECM Take-up Rate	Δ in Predicted HECM Take-up Rate	%Δ in Predicted HECM volume	Predicted T&I Default Rate	Δ in T&I Default Rate	% Δ in T&I Default Rate[2]
Predicted Rates Before Policy	0.681			0.163		
	0.667 - 0.695			*0.154 - 0.173*		
Predicted rates after initial withdrawal limit	0.629	-0.052	-7.6%	0.134	-0.029	-17.8%
	0.619 - 0.639			*0.125 - 0.144*		
Predicted Rates After Policy: Credit Score						
Hard limit: credit score >= 500	0.659	-0.022	-3.2%	0.147	-0.016	-9.8%
	0.645 - 0.673			*0.138 - 0.156*		
LESA for credit score less than 500[1]	0.672	-0.009	-1.3%	0.144	-0.020	-12.0%
	0.657 - 0.687			*0.135 - 0.153*		
LESA for credit score <= 500 + initial draw limit	0.621	-0.060	-8.9%	0.117	-0.047	-28.5%
	0.610 - 0.631			*0.108 - 0.125*		
Hard limit: credit score >= 580	0.599	-0.082	-12.0%	0.115	-0.049	-29.8%
	0.584 - 0.614			*0.107 - 0.122*		
LESA for credit score less than 580	0.652	-0.029	-4.2%	0.103	-0.060	-37.0%
	0.637 - 0.667			*0.096 - 0.110*		
LESA for credit score <= 580 + initial draw limit	0.601	-0.080	-11.7%	0.082	-0.082	-49.9%
	0.590 - 0.613			*0.075 - 0.089*		
Predicted Rates After Policy: Credit Profiles						
Hard limit: drop observations with bad credit[3]	0.563	-0.118	-17.3%	0.115	-0.048	-29.5%
	0.548 - 0.578			*0.107 - 0.123*		
LESA for bad credit	0.642	-0.039	-5.7%	0.098	-0.065	-39.8%
	0.627 - 0.657			*0.091 - 0.105*		
LESA for bad credit + initial draw limit	0.591	-0.090	-13.2%	0.078	-0.085	-52.0%
	0.580 - 0.603			*0.072 - 0.085*		

N = 14,159. Confidence interval in italics. 95% bootstrapped normal-approximation confidence intervals are based on 100 replications.

[1]The change in T&I default rate after LESA is calculated by assuming 0% default for those borrowers falling below the threshold who can

afford the LESA, and otherwise dropping borrowers from the HECM pool who fall below the threshold and cannot afford LESA. This assumes that all borrowers who fall below the threshold and can afford LESA will behave the same as before which is modeled by the bivariate probit model. Those who pass the threshold are also assumed to have the same behavior.

[2]The % change in T&I default rate is the change in the default rate from imposing the pct draw limit or the threshold (if applicable), divided by the baseline default rate.

[3]Bad credit includes any record of delinquent mortgage, in foreclosure, tax lien, delinquent installment debt or delinquent revolving debt.

Table 6: Policy Simulations: Predicted Default Probability Conditional on HECM, Weighted, Severe-Default

		Δ in predicted HECM Take-up Rate	%Δ in Predicted HECM volume	Predicted T&I Default Rate	Δ in T&I Default Rate	% Δ in T&I Default Rate
Predicted Rates Before Policy	0.680			0.070		
	0.667 - 0.694			*0.064 - 0.076*		
Predicted rates after initial withdrawal limit	0.629	-0.051	-7.5%	0.056	-0.014	-20.0%
	0.620 - 0.638			*0.050 - 0.062*		
Predicted Rates After Policy: Credit Score						
Hard limit: credit score >= 500	0.659	-0.021	-3.1%	0.061	-0.009	-12.9%
	0.645 - 0.673			*0.055 - 0.067*		
LESA for credit score less than 500	0.672	-0.008	-1.2%	0.060	-0.010	-14.3%
	0.658 - 0.685			*0.054 - 0.066*		
LESA for credit score <= 500 + initial draw limit	0.621	-0.059	-8.7%	0.047	-0.023	-32.9%
	0.611 - 0.630			*0.042 - 0.053*		
Hard limit: credit score >= 580	0.599	-0.081	-11.9%	0.045	-0.025	-35.7%
	0.584 - 0.614			*0.040 - 0.050*		
LESA for credit score less than 580	0.652	-0.028	-4.1%	0.041	-0.029	-41.4%
	0.638 - 0.666			*0.036 - 0.045*		
LESA for credit score <= 580 + initial draw limit	0.601	-0.079	-11.6%	0.032	-0.038	-54.3%
	0.592 - 0.611			*0.027 - 0.036*		
Predicted Rates After Policy: Credit Profiles						
Hard limit: drop observations with bad credit	0.563	-0.117	-17.2%	0.046	-0.024	-34.3%
	0.548 - 0.577			*0.041 - 0.050*		
LESA for bad credit	0.642	-0.038	-5.5%	0.039	-0.031	-44.3%
	0.628 - 0.656			*0.035 - 0.043*		
LESA for bad credit + initial draw limit	0.591	-0.089	-13.0%	0.030	-0.040	-57.1%
	0.582 - 0.601			*0.027 - 0.034*		

N = 14,159. Confidence interval in italics. 95% bootstrapped normal-approximation confidence intervals are based on 100 replications.

Appendix A: Derivation of the Likelihood Function

There are 3 cases.

		case 1	case 2	case 3
y_{i1}	HECM take-up	1	1	0
y_{i2}	default	1	0	×
w_i	initial draw	observed	observed	×

- Case 1: the household selects a HECM, $y_{i1}=1$, withdraws w_i, and defaults, $y_{i2}=1$. The joint density is

$$
\begin{aligned}
l_{i1}(\theta) &= f(\mathrm{y}_{i1}=1, \mathrm{y}_{i2}=1, \mathrm{w}_i=\mathrm{w} | \mathrm{x}_{i1}, \mathrm{x}_{i2}, \mathrm{x}_{i3}, \mathrm{z}_i) \\
&= \int_{-x_{i1}'\beta_1 - z_i'\alpha_1} \int_{-x_{i2}'\beta_2 - z_i'\alpha_2 - w_i\gamma} \phi_3(u_1, u_2, w - x_{i3}'\beta_3 - \mathrm{z}_i'\alpha_3) du_2 du_1 \\
&= \int_{-x_{i1}'\beta_1 - z_i'\alpha_1} \int_{-x_{i2}'\beta_2 - z_i'\alpha_2 - w_i\gamma} \phi_{u_1,u_2|u_3=w-x_{i3}'\beta_3 - z_i'\alpha_3}(u_1, u_2) f(\mathrm{w} | x_{i3}, \mathrm{z}_i) du_2 du_1 \\
&= f(\mathrm{w} | x_{i3}, \mathrm{z}_i) \int_{-x_{i1}'\beta_1 - z_i'\alpha_1} \int_{-x_{i2}'\beta_2 - z_i'\alpha_2 - w_i\gamma} \phi_{u_1,u_2|u_3=w-x_{i3}'\beta_3 - z_i'\alpha_3}(u_1, u_2) du_2 du_1 \\
&= f(\mathrm{w} | \mathrm{x}_{i3}, \mathrm{z}_i) \mathrm{P}(\mathrm{y}_{i1}=1, \mathrm{y}_{i2}=1 | \mathrm{x}_{i1}, \mathrm{x}_{i2}, \mathrm{x}_{i3}, \mathrm{z}_i, \mathrm{w}_i=\mathrm{w})
\end{aligned}
$$

Here, ϕ_3 is the density of trivariate normal distribution with mean $\begin{bmatrix} 0 & 0 & 0 \end{bmatrix}$ and variance Σ as in Eq. (4). Then the trivariate normal density is written as a product of the marginal density of u_{i3} and the conditional density of u_{i1}, u_{i2} on $u_{i3} = w - x_{i3}'\beta_3 - z_i'\alpha_3$. The terms in the last equation are

$$
\log f(w_i = w | x_{i3}, \mathrm{z}_i) \propto -\frac{1}{2}\log\sigma^2 - \frac{1}{2\sigma^2}(w - x_{i3}'\beta_3 - \mathrm{z}_i'\alpha_3)^2,
$$

$$
\log P(y_{i1}=1, y_{i2}=1 | x_{i1}, x_{i2}, x_{i3}, \mathrm{z}_i, w_i = w) = \log\Phi_2(x_{i1}'\beta_1, x_{i2}'\beta_2 + \mathrm{z}_i'\alpha_2 + w_i\gamma_2; \bar{\mu}_{i,1}, \bar{\Sigma}_1)
$$

where $\phi_2(\cdot,\cdot;\bar{\mu}_{i,1},\bar{\Sigma}_1)$ is the cdf of a bivariate normal $(\bar{\mu}_{i,1},\bar{\Sigma}_1)$. Using the properties of a multivariate normal distribution,

$$
\bar{\mu}_{i,1} = \begin{pmatrix} -1 & 0 \\ 0 & -1 \end{pmatrix} \Sigma_{12}\Sigma_{22}^{-1}(\mathrm{w}_i - x_{i3}'\beta_3) = \begin{pmatrix} -\dfrac{\rho_{13}}{\sigma} \\ -\dfrac{\rho_{23}}{\sigma} \end{pmatrix} (\mathrm{w}_i - \mathrm{x}_{i3}'\beta_3 - \mathrm{z}_i'\alpha_3)
$$

$$
\bar{\Sigma}_1 = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21} = \begin{pmatrix} 1-\rho_{13}^2 & \rho_{12} - \rho_{13}\rho_{23} \\ \rho_{12} - \rho_{13}\rho_{23} & 1-\rho_{23}^2 \end{pmatrix}
$$

where $\Sigma_{11} = \begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{pmatrix}$, $\Sigma_{22} = \sigma^2$, and $\Sigma_{12} = \begin{pmatrix} \rho_{13}\sigma \\ \rho_{23}\sigma \end{pmatrix}$.

- Case 2: the household selects a HECM, $y_{i1}=1$, withdraws w_i and does not default, $y_{i2}=0$. The derivation of the likelihood is similar to that in case 1.

$$\begin{aligned} l_{i2}(\theta) &= \mathrm{P}(\mathrm{y}_{i1}=1, y_{i2}=0, w_i=w \mid x_{i1}, x_{i2}, \mathrm{x}_{i3}, \mathrm{z}_i) \\ &= f(\mathrm{w}_i=\mathrm{w} \mid \mathrm{x}_{i3}, \mathrm{z}_i)\,\mathrm{P}(\mathrm{y}_{i1}=1, y_{i2}=0 \mid x_{i1}, x_{i2}, x_{i3}, \mathrm{z}_i, \mathrm{w}_i=w) \end{aligned}$$

with

$$\log f(\mathrm{w}_i=w \mid x_{i3}, \mathrm{z}_i) \propto -\frac{1}{2}\log\sigma^2 - \frac{1}{2\sigma^2}(\mathrm{w}_i - x_{i3}'\beta_3 - \mathrm{z}_i'\alpha_3)^2$$

$$\log P(\mathrm{y}_{i1}=1, \mathrm{y}_{i2}=0 \mid x_{i1}, x_{i2}, x_{i3}, \mathrm{z}_i, \mathrm{w}_i=w) = \log\Phi_2(\mathrm{x}_{i1}'\beta_1, -x_{i2}'\beta_2 - \mathrm{z}_i'\alpha_2 - \mathrm{w}_i\gamma; \bar{\mu}_{i,2}, \bar{\Sigma}_2)$$

where as in Case 1,

$$\bar{\mu}_{i,2} = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix}\Sigma_{12}\Sigma_{22}^{-1}(\mathrm{w}_i - x_{i3}'\beta_3 - \mathrm{z}_i'\alpha_3) = \begin{pmatrix} -\dfrac{\rho_{13}}{\sigma} \\ \dfrac{\rho_{23}}{\sigma} \end{pmatrix}(\mathrm{w}_i - x_{i3}'\beta_3 - \mathrm{z}_i'\alpha_3),$$

$$\bar{\Sigma}_2 = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix}(\Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})\begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 1-\rho_{13}^2 & -\rho_{12}+\rho_{13}\rho_{23} \\ -\rho_{12}+\rho_{13}\rho_{23} & 1-\rho_{23}^2 \end{pmatrix}.$$

- Case 3: the household does not take up HECM, $y_{i1}=0$.

$$l_{i3}(\theta) = \mathrm{P}(\mathrm{y}_{i1}=0 \mid x_{i1}, \mathrm{z}_i) = \Phi_1(-x_{i1}'\beta_1 - \mathrm{z}_i'\alpha_1; 0,1),$$

where $\Phi_1(\cdot;0,1)$ is the cdf of standard normal distribution.

The full likelihood function is:

$$\log L_n(\theta) = \sum_{i=1}^n \left\{ I(\mathrm{y}_{i1}=1, y_{i2}=1)\log \mathrm{l}_{i1}(\theta) + \mathrm{I}(\mathrm{y}_{i1}=1, y_{i2}=0)\log \mathrm{l}_{i2}(\theta) + \mathrm{I}(\mathrm{y}_{i1}=0)\log \mathrm{l}_{i3}(\theta) \right\}.$$

In the maximum likelihood estimation, ρ_{12}, ρ_{13}, ρ_{23} and σ are not directly estimated. Directly estimated is a transformation of these parameters, $\log\sigma$ for σ and $\mathrm{atanh}\rho = \frac{1}{2}\log\left(\frac{1+\rho}{1-\rho}\right)$ for ρ.

Thus $\rho = \dfrac{-1+\exp(2\mathrm{atanh}\rho)}{1+\exp(2\mathrm{atanh}\rho)}$. The parameter space of the transformed variable is therefore unrestricted.

Appendix B: Variable Definitions

Variable Name	Definition
Ever-default	Coded 1 if the borrower ever entered technical default on their HECM from the time of origination through June 30, 2014. Technical default occurs when the lender is forced to make a corporate advance to pay for the borrower's property taxes and/or homeowners insurance because (1) the borrower failed to make the payments, and (2) there are no remaining funds on the HECM (balance owed is equal to the principal limit).
Severe-default	Coded 1 if borrower entered technical default and had an outstanding balance for property taxes and/or insurance payments advanced by the lender on behalf of the borrower of $2,000 or more as of June 30, 2014.
Monthly income	Self-reported monthly household income at the time of counseling
Non-housing assets	Self-reported household non-housing assets at the time of counseling, including the value in checking and savings accounts, retirement accounts and the value of non-housing property
Property tax amount	Three-year average (2008-2010) of county level property tax rates (from The Tax Foundation) multiplied by house values
Property taxes/income	Property tax amount (as defined above), divided by household income
FICO credit score	FICO credit score as reported in Equifax credit data; ranges from 300 to 850; measured in hundreds
Revolving balance/income	From credit attribute file, outstanding balance on revolving debt at the time of counseling, divided by annual household income
Installment balance/income	From credit attribute file, outstanding balance on installment debt at the time of counseling, divided by annual household income
Monthly mortgage payments	From credit attributes file, calculated as the total of all minimum monthly mortgage payments (first and second liens and HELOCs)
Foreclosure started	From credit attribute file, coded 1 if the borrower had a foreclosure in process when they completed counseling
Bankruptcy in last 12 months	From credit attribute file, coded 1 if the borrower had a bankruptcy in the 12 months prior to counseling
Available revolving credit	From credit attribute file, constructed as the total revolving credit limit less the total outstanding revolving balance
No revolving credit	From credit attribute file, coded 1 if the borrower had no revolving credit accounts on his/her credit file
Mortgage past due, 2+ months	From credit attribute file, coded 1 if the amount of the past due mortgage is equal to or greater than twice the monthly mortgage payment amount
Tax lien or judgment	From credit attribute file, coded 1 if the borrower had a tax lien or judgment on their credit report file at the time of counseling.
Hispanic	Indicator for ethnicity, Hispanic
Race, white	Indicator for race, Caucasian
Race, black	Indicator for race, Black
Race, Asian	Indicator for race, Asian
Unmarried male	Indicator for single male household; includes never married, divorced, widowed and separated
Unmarried female	Indicator for single female household; includes never married, divorced, widowed and separated
Age, youngest household member	Age of the youngest household member at the time of counseling; if single, age of counselee

First language, not English	Indicator for the first language of the client is other than English
Education, bachelors	Indicator for highest level of education completed, 4 year college
Education, high school	Indicator for highest level of education completed, high school or GED
Education, adv. degree	Indicator for highest level of education completed, graduate degree
Education, some college	Indicator for highest level of education completed, 2 year degree or some college
Initial withdrawal %	From HUD data, the proportion of the actual IPL withdrawn within the first month after origination
Estimated IPL	Estimated initial principal limit (IPL), calculated based on the lesser of the self-reported home value at the time of counseling or the county specific FHA loan limit and the principal limit factor at the time of counseling adjusted for the borrower's age. For the principal limit, we use the greater of the principal limit factor calculated using the average adjustable expected interest rate or the principal limit factor using the average fixed interest rate as of the day of counseling
Estimated home value-IPL	Calculated as the difference between the self-reported home value at the time of counseling and the IPL. Only contains non-negative values.
Home value exceeds MCA	Coded 1 if the self-reported home value at the time of counseling is greater than the Maximum Claim Amount (MCA) limit established by HUD for the county and year.
Mortgage debt/Estimated IPL	Self-reported total mortgage debt at the time of counseling divided by the estimated IPL
HELOC indicator	From credit attributes file, coded 1 if the borrower had a HELOC on the credit file at the time of counseling
State house price deviation	From state level FHFA data, deviation of the current real house price from the average real house price for the 1980 to 1999 period
State house price volatility	From state level FHFA data, house price volatility calculated based on the nine years prior to the year of counseling
State GDP growth	A state's real GDP growth rate
Exposure days	Calculated as the number of days since the time of HECM origination and July 1, 2014 or the date of termination on the loan, whichever comes first.
Actual IPL	From HUD, the actual initial principal limit at the time of origination
Appraised value-IPL	Calculated as the difference between the appraised value (from HUD) of the home at the time of origination less the actual IPL
Mortgage debt/Actual IPL	Calculated as the total amount of mortgage debt at the time of origination from the credit attributes file, divided by the actual IPL from HUD
HPI Δ, N year	Percentage change in real house price index (HPI) N years after origination from the HPI in the year of origination. HPI is from FHFA's "All transactions not seasonally adjusted index," deflated by the CPI.
Fixed rate policy indicator	Coded 1 if the origination occurred on or after April 1, 2009, when the fixed rate, full-draw HECM product became readily available in the market
Fixed rate policy*spread	Calculated as the spread between the average fixed and adjustable interest rates as of the month of HECM application, multiplied by the fixed rate policy indicator