HAMP, Home Attachment, and Mortgage Default

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Abstract

This paper studies the Homeowner Affordability Modification Program (HAMP), a 2009 federal program reducing delinquent household mortgage payments to 31 percent of monthly income. To assess the program I propose and estimate a structural model of mortgage default using program results. The model allows for income, house prices, and exit preference shocks to induce default, and allows homeowners to vary by an unobserved permanent attachment, or sentimental, value to their home. Counterfactual simulations suggest HAMP has prevented 515,354 defaults as of June 2013 at an expected five-year cost per prevented default of $41,096. Back-of-the-envelope calculations estimate the social cost of foreclosure at $16,000 suggesting a net program loss of $12.7 billion. Extrapolating simulation results, I find the program needs to raise the target payment level to 52 percent of monthly income to become socially beneficially.

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1 Introduction

Between June 2006 and March 2009, US house prices fell by 30 percent, the largest national house price decline in nearly a century, and as a result 25 percent of US mortgages became underwater.[1] Underwater homeowners, whose home is worth less than their mortgage debt, face the tough decision of whether to continue making mortgage payments or to default on the mortgage and walk away from their home. Mortgage default and the resulting foreclosure are costly to lenders, borrowers, and local governments. One estimate finds average foreclosure costs are $79,443.[2] In 2008, 2.3 million homeowners were foreclosed upon, a stark increase from historical norms. The catastrophic financial sector and social damage caused by the foreclosure spike prompted government officials to seek a remedy.

This paper studies the 2009 Homeowner Affordability Modification Program (HAMP), the largest federal response to the foreclosure crisis. HAMP is a subsidized mortgage modification process reducing housing payments to 31 percent of monthly income for its 1.1 million participants. HAMP offers large benefits relative other federal assistance programs. For example, the 2012 earned income tax credit had a maximum credit of $5,891 and average maximum temporary assistance for needy families benefits are $5,200. The average HAMP participant potentially saves $9,900 annually on mortgage payments.

This paper analyzes HAMP by quantifying its benefits in terms of defaults prevented compared to a benchmark policy where participants are offered no housing payment reduction. Simulation results using estimated parameter values find HAMP has prevented 515,354 defaults as of June 2013 and expects to prevent 505,803 defaults after five years. Expected five-year program costs of $20.8 billion means HAMP will pay $41,096 per prevented default. Back-of-the-envelope calculations estimate foreclosure externalities cost society $16,000, implying a social loss of $12.7 billion.

Recent work by Agarwal et al. (2017) also examine HAMP and quantify the number of foreclosures it prevents. They exploit HAMP eligibility cutoffs to measure HAMPs effect on foreclosure rates using a difference-in-difference strategy. However, a difference-in-difference strategy relies critically on locating a credible control group. This is a difficult task, as HAMP is a national program without the large kinks typically exploited to measure treatment effects. Agarwal et al. (2017) use HAMP restrictions on the mortgage occupancy status, mortgage balance, and net present value of modification to estimate treatment effects of accepted versus rejected applicants. Estimating treatment

[1] http://www.corelogic.com/about-us/news/new-corelogic-data-shows-slight-decrease-in-negative-equity.aspx

[2] Apgar and Duda (2005)

effects across these dimensions may not be representative of the average HAMP treatment effect, and in turn limits the program evaluation.

Other research on HAMP include Scharlemann and Shore (2016) and Ganong and Noel (2017). Scharlemann and Shore (2016) use a regression kink design within HAMP to estimate the effect of principal forgiveness on default. Among HAMP modifications receiving the "Principal Reduction Alternative" they find that principal forgiveness reduced default rates by eighteen percent relative to the standard HAMP modification. Ganong and Noel (2017) study HAMP using bank records and credit reports while utilizing a regression discontinuity design. They find that HAMP had no effect on default or consumption among borrowers with negative equity.

To quantify defaults prevented by HAMP, this paper uses the responsiveness of participants to default with respect to variation in their mortgage value. To determine the value of a set of mortgage terms I use a structural model of the mortgage default choice. Households solve an optimal default decision model in a dynamic discrete choice framework and underlying structural parameter values are estimated using variation in default rates in relation to observable household and mortgage characteristics.

An advantage of estimating a structural model to evaluate HAMP compared to the reduced form methods of Agarwal et al. (2017) and Scharlemann and Shore (2016) is that the results are more broadly representative of the treatment group. For instance, in Agarwal et al. (2017) continuous treatment groups include the mortgage balance cutoff, but fewer than one percent of HAMP participants are within \$100,000 of the \$729,750 HAMP eligibility cutoff. Similarly, they exploit marginal applicants in a narrow range around the Net Present Value cutoff, but as a result are by definition ignoring participants who lenders expect to receive the largest HAMP benefit. Instead of estimating the benefit of HAMP, Scharlemann and Shore (2016) estimate the benefit of principal forgiveness within HAMP that accounts for only ten percent of HAMP participants. This paper utilizes large within-HAMP variation in the assigned mortgage modification value to estimate parameter values and determine the program costs and benefits. Results will better reflect the benefits and cost of the average, as opposed to marginal, participant.

Another advantage of using a structural model is that I can run counterfactural policy experiments using estimated parameter values. Since the primary HAMP treatment effect is to set housing cost to 31 percent of income, I run counterfactual policy experiments testing how alternative payment levels would affect program default rates. Performing these simulations show how much defaults respond to adjusting the payment level or whether bigger structural changes, such as a focus on principal reduction, are required to reduce default rates. Simulations raising the HAMP target housing payment level from 31 percent to 38 percent increase program defaults by 141,075 while lowering the level to 25 percent prevents an additional 89,032 defaults. These counterfactual simulation results are also used to derive the optimal target housing payment level as a function of foreclosure externality costs.

Lastly, this paper aims to gain a better understanding of mortgage default choices. The average HAMP participant owes $54,514 more on the mortgage balance than its market price yet many continue to pay off the mortgage balance. Despite the seemingly large financial burden, there is a variety of reasons underwater homeowners may continue making mortgage payments. Households may have a sentimental attachment to their home, valuing it above the market price. The household also considers the relative economic benefit of remaining in the home to exiting and moving into the rental market. Households experiencing large permanent income shocks may wish to re-optimize their housing consumption, which cannot be done without existing their current home. Mortgage payments also preserve the option value of future default. The opportunity cost of a few hundred dollars today must be weighed against the potential gain of thousands of dollars if future house prices increase.

This paper uses HAMP participants to estimate the distribution of home attachment values and idiosyncratic home exit preference shocks among homeowners. Doing so quantifies the impact of a permanent heterogeneity across households in observed defaults as opposed to randomness in the mortgage exit decision unaccounted for by mortgage value or income and house price shocks. Knowing the home attachment distribution is important in understanding program results. A justification for the focus on easing liquidity constraints in HAMP is a credit market failure which could force people to leave a home they value dearly during a financially vulnerable period. The prevalence of liquidity constraints in mortgage default are unknown and are notoriously difficult to observe. But many factors contribute to mortgage default, and even if households have the ability to make mortgage payments they may not have the desire to. A low average value or a high degree of heterogeneity in home attachment across participants indicates many households place little sentimental value on their home and simply choose to default soon after home prices drop. All foreclosures impose costs on society, but these strategic default choices are less concerning from a public policy standpoint.

The effectiveness of a mortgage modification program rests crucially on the ability of mortgage value to influence the home exit decision. If the natural evolution of household home preferences trumps variation across households in mortgage value, reducing housing payments will have limited effect on defaults after liquidity constraints are eased. But if reducing a mortgage interest rate by several percentage points can entice the households to remain in the home a few extra years, enough equity could be gained that the mortgage then is paid off instead of default upon exit and saves the public thousands in foreclosure costs.

The empirical contribution of this paper is important because it is the first structural estimation of a dynamic mortgage default model. The proposed default model is based on Campbell and Cocco (2011) where households consider housing prices, rental markets, income, and assets when making mortgage payment and savings decisions. I build upon the model by allowing households to vary by an unobserved home attachment value, systematic variation in rental market, and idiosyncratic home exit preference shocks. Further, my estimation considers household-level payment history instead of matching aggregated data moments and implementation includes finer household-level financial details, such as the existence of second mortgages, other debt obligations, and credit score. While Campbell and Cocco (2011) focuses on the impact of loan-to-value ratios, loan-to-income ratios, and mortgage products on default rates, I calculate the mortgage value by solving an optimal decision problem. In doing so, I uncover estimates of unobserved factors in the default decision, allowing realistic counterfactual policy simulations.

Estimating the home attachment distribution also contributes to migration literature. Estimation results are consistent with findings of papers such as Kennan and Walker (2011) that estimate large moving costs which vary considerably across households. This paper identifies the cost of moving across state lines, but combines the cost of leaving a home with the cost of leaving social and labor market networks or other attachments to the area. Households defaulting on their mortgage are only forced to exit their current home, but may very likely remain in the same metro area and could in theory just move across the street. Molloy and Shan (2010) find only 20 percent of households foreclosed upon relocate to a new labor market. Gregory (2011) also finds a large locational preferences among New Orleans residents who rebuild their homes destroyed in the Katrina hurricane. However, the home attachment value estimated in this paper is unique because it represents the value to remaining in a specific house.

Lastly, this paper further contributes to empirical housing literature by differentiating between the roles of rental housing prices and expected rental price growth in house prices. Households with the exact same mortgage and home value, but differing in location, can vary significantly in the value of their mortgage depending on rental price levels. An analogy is comparing similarly priced high-growth and low-growth stocks where the difference in stock value comes from the portion of stock value attributed to expected future dividends versus current dividends. This difference comes into play when households decide whether to exercise the default option on their mortgage. Ceterus peribus, locations with lower expected house price growth imply higher current period consumption value, making mortgage payments more valuable. Home values are divided between rental prices and expected price gains at the metro level using rent-to-price ratios reported by the data company Zillow.

HAMP is a unique program, born from the financial chaos and uncertainty during the Great

Recession. Both as a federal program and more broadly among mortgage modifications, HAMP dives into unknown territory. Previous modifications typically increased housing payments while HAMP drastically reduces them, often by thirty percent or more. This provides a great experiment to examine the default decision, uncovering the sources of mortgage default and learning about underlying home attachment and idiosyncratic exit preferences households possess.

2 HAMP Overview

A federal program targeting mortgage default prevention never existed prior to the 2007 housing bust. Several papers including Posner and Zingales (2009) and Campbell et al. (2009) document possible negative externalities or deadweight losses associated with foreclosure. During the bust, policy makers became worried that private lender mortgage modification rates were socially suboptimal as they did not internalize these externalities.

After US foreclosures reached unprecedented levels in 2008, several initial federal programs were crafted to combat rising defaults. These programs provided limited assistance and were eventually viewed unsuccessful due to low take-up and poor performance.[3] In November 2008, the Federal Deposit Insurance Corporation began the "Mod-in-a-Box" program which served as the pre-cursor to HAMP. This program focused on easing liquidity constraints by reducing monthly payments relative to current income for delinquent mortgages owned by IndyMac Bank.[4] Just five months later the program gained enough political traction to form the basis of the national program HAMP in March 2009.

Strictly speaking, HAMP is a federally subsidized mortgage modification process. Eligible participants have their monthly housing payments reduced to 31 percent of monthly income and retain the modified terms until becoming 90 days delinquent on the mortgage or the loan balance is paid off.[5] [6] HAMP eligibility requires some basic housing characteristics (i.e. owner-occupied, first lien, single-family home), current housing payments greater than 31 percent of income, and passing a Net Present Value (NPV) calculation. The NPV calculation is meant to ensure the modification is in the

[3]These programs include HOPE for Homeowners, FHASecure, and the "Teaser Freezer" program. HOPE for Homeowners, estimated to assist 400,000 households, was particularly unsuccessful as only 451 households participated.

[4]IndyMac had been placed into conservatorship by the Federal Deposit Insurance Corporation in July 2008 from liquidity concerns.

[5]Housing payments are defined as payment on the primary mortgage, real estate taxes, homeowners insurance, and association dues and fees. HAMP modifications only affect the primary mortgage payments.

[6]To be precise, the modified mortgage terms remain constant for five years, after which the interest rate on the mortgage may gradually rise to meet the market interest rate at the time of modification.

lenders best interest and eliminates lender discretion in the acceptance of participants with a positive NPV.[7] Lenders are compensated for participation by receiving a fifty percent subsidy payment for the monthly payment reduction (capped at 3.5% of borrower monthly income) along with a lump-sum per modification. Additional eligibility requirements and program details are provided in the Appendix.[8]

Designing an effective mortgage modification program faced many problems, summarized well in Cordell et al. (2009). Prior private mortgage modifications typically increased monthly payments by re-capitalizing delinquent arrears and performed poorly, with 50 percent of modifications re-defaulting within 12 months according to Haughwout et al. (2009) and Quercia et al. (2009). Lack of evidence on effective modifications led to fierce debate on program design. HAMP focused on easing possible liquidity constraints by reducing housing payments relative to income, an often cited but difficult to verify cause of mortgage default. The program also needed to offer compensation to entice lender and borrower participation while navigating legalities of pooling and servicer agreements of securitized mortgages.

As of June 2013, 1.1 million households received a permanent mortgage modification through HAMP.[9] Among participants, 306,100 or 27 percent defaulted out of HAMP while 15,929 or 1.4 percent paid off their mortgage balance. Figure 1 displays HAMP enrollment over time by June 2013 payment status. Nearly half of HAMP participants enrolled in 2010, peaking in March 2010. HAMP participation displays strong regional variation. Figure 2 shows participation levels and rates relative to population. The four states hit hardest by the housing bust, California, Florida, Nevada, and Arizona, represent 39 percent of HAMP participants while containing 21 percent of the US population.

3 Model

In this section I propose a model of the household mortgage default decision. The environment reflects one facing a HAMP participant, or more generally, a household following a large negative house price shock.

[7] Lenders have discretion on acceptance for those not passing the Net Present Value calculation. About 85 percent of otherwise eligible applications pass the Net Present Value test and half of the others are accepted into the program anyway through lender discretion.

[8] Full program documentation can be found at `https://www.hmpadmin.com/portal/programs/docs/hamp_servicer/mhahandbook_40.pdf`

[9] An additional 800,000 households began but dropped out during the trial period before the modification becomes official.

3.1 Framework, Timing, and Preferences

I model the mortgage default decision facing homeowners using a finite horizon, discrete time framework. Households begin endowed with a home and a mortgage, and decide each period whether to exit the home in addition to a savings decision. Upon exit, households make rental housing decisions. Households receive an exogenous income stream and have expectations about housing prices which are a combination of current rental prices and expected rental price growth. Four shocks are realized each period: an idiosyncratic exit preference shock, income shock, rental price shock, and rental price growth rate shock. Homeowners solve the default decision as an optimal stopping problem, waiting for a large exit shock to make leaving the home appealing.

3.1.1 Mortgage

A household i begins at time $t=0$ endowed with a property H and a corresponding primary mortgage M_1. The mortgage is a debt repayment contract consisting of an interest rate R^M, term length T^M, principal balance $B^M(t)$, and forbearance percentage F^M and requires monthly payment $P_1^M = \frac{R^M B^M(t)}{1-(1+R^M)^{-T^M}}$. [10] The mortgage is exited either by paying off the balance or not making payments.

A household may also be endowed with a second mortgage M_2. For simplification, this mortgage consists of a time-invariant balance B_2^M and monthly payment P_2^M. A second mortgage is assumed tied to the primary mortgage, so a household must either pay off both mortgages or default on both mortgages when exiting.

3.1.2 Homeownership

To remain in their home, a household must make total housing payments P^M each period consisting of the primary mortgage payment P_1^M, a possible second mortgage payment P_2^M, and other housing expenses δ_ℓ which are a fraction of the home value $p_t(H,\ell)$:

$$P^M = P_1^M + P_2^M + \delta_\ell p_t(H,\ell)$$

[10] Forbearance is not a typical mortgage feature, but is part of the HAMP mortgage modification process. Forbeareance means a fraction of the original principal balance $F^M B^M(0)$ becomes a non-interest bearing balloon payment, due with the final mortgage payment.

If a household decides to sell their home, they receive the current market price $p_t(H,\ell)$ but must pay a sales cost s, realized as a percentage of the sales price. Conditional on exiting the home, a household will sell their home only if proceeds cover the mortgage balance, forbeared amount, second mortgage balance, and sales cost. Otherwise the household will default on the mortgage.[11]

The mortgage is non-transferable. When under the mortgage a property can not be rented.[12] Households are not able to expand or contract their current home size without exiting the mortgage. The focus of this paper is on mortgage default so the model abstracts from the initial housing choice, the decision whether to rent or buy a future property, and the possibility of mortgage refinance.[13] These are straightforward extensions of the model available for future research considering the broader scope of housing market choices.

3.1.3 Income

Households are endowed with an initial monthly income $I_{i,0}$. Each period, the household receives an income related to their previous income by ρ, and is altered based on locational and idiosyncratic shocks $\omega_{\ell,t}$ and $\kappa_{i,t}$ respectively:

$$\log I_{i,t} = \rho \log I_{i,t-1} + \omega_{\ell,t} + \kappa_{i,t} \tag{1}$$

Households income can be saved or spent each period on non-durable consumption C_t and housing payments P^M. Income taxes, τ, must also be paid each period as a percentage of household income.

3.1.4 Assets

Assets A_t, representing easily liquidated financial assets such as cash, stocks, and bonds, can be used to purchase consumption and make housing payments. Assets not spent each period are invested, receiving a constant, risk-free market rate of return, r^f. Aside from the endowed mortgages, there are no other borrowing or lending opportunities available, so $A_t \geq 0 \; \forall \, t$.

[11] While not considered in this paper, households may be willing to include additional assets to the sales proceeds in order to pay off the mortgage as opposed to defaulting. Foote et al. (2008) find that homeowners rarely default with less than ten percent negative equity. Social stigma attached to default could factor into this decision, which Guiso et al. (2009) document based on survey responses. In contrast though, households could prefer foreclosure to a sale even if sale proceeds could cover the mortgage obligations. Some states such as New York and Illinois take well over a year to process a foreclosure, during which the household gets to live in the home rent free, making foreclosure potentially more attractive than a sale.

[12] This is due to legal restrictions.

[13] Note that refinancing is unlikely for HAMP participants given 70 percent of participants receive a two percent interest rate.

3.1.5 Other Debt Obligations

Each household is endowed with an other debt obligation amount D which must be paid each period, reducing discretionary income. These obligations represent required debt payments aside from the housing payment such as car loans, student loans, or medical-related debts. I allow no choice in making other debt payments. Renters are guaranteed a minimum consumption level $\{\underline{C},\underline{H}\}$ if income and assets are lower than D.

3.1.6 Prices and Budget Constraint

Non-durable consumption C_t may be purchased using current income and financial assets at the price level of consumption P_t. The price level of consumption P_t is constant across locations, and evolves with a constant inflation rate π:

$$P_{t+1} = P_t(1+\pi)$$

Housing H is a continuous good representing flow value of housing services received from living in the home. Rental housing is a spot market, where renters can costlessly adjust H once per year. The rental cost of housing $r_t(H,\ell)$ is the rental price level per unit of housing $R_{\ell,t}$ times the house size H:

$$r_t(H,\ell) = R_{\ell,t}H$$

The log rental price level of housing varies over time and location, ℓ. The rental price process includes both a trend component $\nu_{\ell,t}$ and location-specific i.i.d shock $\varepsilon_{\ell,t}$:

$$\log R_{\ell,t} = \log R_{\ell,t-1} + \nu_{\ell,t} + \varepsilon_{\ell,t} \tag{2}$$

$$\nu_{\ell,t} = \nu_{\ell,t-1} + \varsigma_{\ell,t}$$

The trend component, or expected growth rate of rental prices $\nu_{\ell,t}$ receives an i.i.d. shock $\varsigma_{\ell,t}$ each period.

Homeowners must satisfy the following periodic budget constraint:

$$\frac{A_{t+1}}{1+r^f} = A_t + I_{i,t}(1-\tau) - P^M - D - P_t C_t$$

Similarly, households in the rental market satisfy the budget constraint:

$$\frac{A_{t+1}}{1+r^f} = A_t + I_{i,t}(1-\tau) - R_{\ell,t}H_t - D - P_t C_t$$

with $A_{t+1} = 0$ if current assets and income can not cover debt payments and minimum consumption levels: $D \geq A_t + I_{i,t}(1-\tau) - r_t(\underline{h}, \ell)$.

3.1.7 Housing Purchase Price

Housing purchase prices are based on the current and expected future stream of rents from the home less property taxes, maintenance costs, and other housing expenses δ_ℓ, realized as a percentage of the home value.[14]

$$\begin{aligned}
p_t(H,\ell) &= E_t[\sum_{r=t}^{\infty} \beta^{r-1}(r_t(H,\ell) - \delta_\ell p_k)] \\
p_t(H,\ell) &= E_t[\sum_{k=t}^{\infty} \beta^{r-1}(R_{\ell,t}H - \delta_\ell p_k)] \\
p_t(H,\ell) &\approx R_{\ell,0}H \sum_{r=t}^{\infty} (\beta^{r-l}(1+\nu_{\ell,t})) - p_t(H,\ell)\frac{\delta}{1-\beta}
\end{aligned}$$

$$p_t(H,\ell) = \frac{R_{\ell,0}H}{(1-\beta(1+\nu_{\ell,t}))(1+\frac{\delta_\ell}{1-\beta})} \tag{3}$$

This is similar to a housing market proposed by Poterba (1984) or a capital-asset pricing model in finance literature.

Price-to-rent ratios $\psi_{\ell,t}$ compare the home purchase price to its monthly rental price in a given location. Given equations (2) and (3) the price-to-rent ratio is proportional to the expected rental price growth rate $\zeta_{\ell,t}$:

$$\begin{aligned}
\psi_{\ell,t} &= \frac{p_t(H,\ell)}{r_t(H,\ell)} \\
&= \frac{\frac{R^H_{\ell,t}H}{(1-\beta(1+\nu_{\ell,t}))(1+\frac{\delta_\ell}{1-\beta})}}{R^H_{\ell,t}H}
\end{aligned}$$

[14] Note that the assumption $p_{\ell,t} = p_{\ell,k} \forall \text{ k } > t$ is used in approximating the expected future tax burden.

$$= \frac{1}{(1-\beta(1+\nu_{\ell,t}))(1+\frac{\delta_\ell}{1-\beta})} \tag{4}$$

Equation (4) relates the price-to-rent ratio $\psi_{\ell,t}$ to the trend component or expected growth rate $\nu_{\ell,t}$ of house prices. It is well known that homes that rent for the same amount in different locations can sell for substantially different amounts Himmelberg et al. (2005). This formulation attributes part of this variation in price-to-rent ratios mechanically to local housing expenses δ_ℓ but attributes the remaining variation to differences in expected house price growth rates. The price-to-rent ratio $\psi_{\ell,t}$ evolves according to:

$$\psi_{\ell,t} = \psi_{\ell,t-1} + \zeta_{\ell,t}$$

3.1.8 Utility

Household utility follows Campbell and Cocco (2011) where periodic utility u_t is separable in housing and consumption, with coefficient of relative risk aversion parameter γ, and relative weights Θ and 1-Θ on housing and non-durable consumption respectively. Agents derive utility from consuming housing H_t and non-durable consumption C_t each period and gain a lump-sum utility from terminal period assets A_T, scaled by a bequest motive, b. A minimum housing consumption level $\underline{h}$ allows the model to capture the elasticity of the housing budget share relative to income:

$$\begin{aligned} u_t &= \alpha\big((1-\Theta)\frac{C_t^{1-\gamma}}{1-\gamma} + \Theta\frac{(H_t-\underline{h})^{1-\gamma}}{1-\gamma}\big) + \xi_i \mathbb{1}_{[H_t=H_0]} + \rho(Z_i)\mathbb{1}_{[H_t=H_0]} + \eta_t(D) \\ u_T &= \alpha\big(b\frac{A_T^{1-\gamma}}{1-\gamma}\big) \end{aligned}$$

Households receive choice-specific exit preference shocks $\eta_t(D)$ each period that depend on the mortgage payment choice $D \in \{\text{pay,exit}\}$. Exit shocks reflect idiosyncratic changes to a household's preference to remain in their home relative to moving into the rental market. Example of such shocks include finding a desirable rental property or gaining a new job across town. The parameter α scales periodic consumption utility relative to the variance of exit preference shocks $\eta_t(D)$.

Households differ in their permanent home attachment value ξ_i. This attachment allows households to value their home higher than its market price. This attachment only exists for the endowed home, lost upon exit. No future attachments can be gained, an extreme assumption but one that reflects the more fluid nature of the rental market. Households vary systematically in their valuation of the rental market by $\rho(Z_i)$, a function of credit and mortgage characteristics Z_i. Households with lower credit scores or higher interest rates may value rental markets differently for reasons not otherwise captured in the model.

3.2 Household Problem

Households move through time making decisions regarding mortgage payment or exit, savings, and if renting, housing consumption. Renters optimize consumption by solving for an optimal housing budget share:

$$\max_{C_t,H_t}(1-\Theta)\frac{C_t^{1-\gamma}}{1-\gamma}+\Theta\frac{(H_t-\underline{h})^{1-\gamma}}{1-\gamma}$$

Households save in order to smooth consumption by equating the marginal value of current period consumption to expected future consumption with expectations about future income and house price levels.

Homeowners make savings and mortgage payment decisions. Similar to renters, households save to smooth consumption over time. Savings also provide insurance against potential liquidity constraints that force households to exit the home. The savings incentive increases with mortgage value.

Considered as a financial asset, the value of a mortgage comes from the housing consumption value and the net sales price, similar to dividend payments and capital gains on stock. Mortgage value from the expected net sales price includes the option to default, placing a lower bound on the net sales price of zero. Total mortgage value also includes the discounted present value of the expected difference in mortgage cost relative to housing consumption, or rental value of the home:

$$\begin{aligned} M(R_t,\nu_t,t) &= \max\nolimits_{\text{default,sell,pay}} \quad \{0, p_t(H)-B^M(t)-F^M B^M(0), r_t(H)-P^M+\beta E[M(R_{t+1},\nu_{t+1},t+1)]\} \\ M(R_T,\nu_T,T) &= \max\nolimits_{\text{default,sell}} \quad \{0, p_t(H)-B^M(t)-F^M B^M(0)\} \end{aligned}$$

When mortgage equity drops negative, default becomes more likely. But mortgage value does not necessarily approach zero even when default becomes certain. Instead mortgage value converges to the discounted value of the difference between mortgage cost and the housing consumption value. This means that households paying less in housing payments than the rental value have no financial reason to ever exit the home, regardless of equity. If housing purchase prices drop significantly in a location because rental price levels dropped, default occurs because both the expected sales price drops and the rental market becomes more attractive. If housing purchase prices drop only because expected rental price growth dropped, default is less likely or delayed because the housing consumption value relative remains unchanged.

The value of a mortgage to households must incorporate other factors in addition to financial considerations. Households may have a sentimental home attachment ξ_i, so they may value the home consumption higher (or lower) than the rental market price. Financial constraints following mortgage default, both in this paper and in reality, may restrict homeowners in re-purchasing their endowed home. Income shocks may cause liquidity constraints or force mortgage exit in a given period. Systematic home preferences $\rho(Z_i)$ may also make renting less attractive than owning. Homeownership insures households against housing demand shocks $\varepsilon_{\ell,t}$ and $\zeta_{\ell,t}$, but renting allows households to adjust housing in response to income shocks $\kappa_{i,t}$ and exit preference shocks $\eta_t(D)$.

3.3 Dynamic Programming Representation

The solution to the household problem may be expressed as a dynamic programming problem, following Bellman (1956). Define the value function $V(X_t, A_t, Y, \eta)$ as a mapping from each state to the expected present discounted value of the subsequent utility associated with an optimal policy choice, where X_t represents the state variables time, income, rental price level, and rent-to-price ratio and Y represents permanent household characteristics. By the principle of optimality, the value function must satisfy the Bellman equation,

$$V(X_t, A_t, Y, \eta) = \max_{A_{t+1}, X_{t+1}} \{u(X_t, X_{t+1}, A_t, A_{t+1}, Y, \eta)\} + \beta \bar{V}(X_{t+1}, A_{t+1}, Y)\} \tag{5}$$

$$\bar{V}(X_t, A_t, Y) = E \max_{\eta} V(X_t, A_t, Y, \eta)$$

Because optimal asset accumulation is independent of the idiosyncratic preference shocks $\eta_t(D)$ equation (5) may be rewritten as:

$$V(X_t, A_t, Y, \eta) = \max_{X_{t+1}} \{u(X_t, X_{t+1}, A_t, A^*, Y, \eta_t(D))\} + \beta \bar{V}(X_{t+1}, A^*, Y)\}$$

where X_t represents the household state at time t, Y is household heterogeneity including their primary and secondary mortgages, debt obligations, age, and location, and $\eta_t(D)$ is the choice-specific exit shock.

A^* is the optimal asset accumulation policy conditional on the household's previous state (X_t, A_t, Y)

and chosen state,(X_{t+1}).

$$A^*(X_t,A_t,Y) = \arg_{A_{t+1}}\{u(X_t,X_{t+1},A_t,A_{t+1},Y,\eta_t(D)) + \beta\bar{V}(X_{t+1},A_{t+1},Y)\} \tag{6}$$

This representation is convenient for estimation as it allows for the liquid assets, unobserved in the data, to be conditioned out of the likelihood function.

Assuming the choice-specific preference shocks $\eta_t(D)$ are drawn from the Type I extreme value distribution allows for a closed form representation of the expected maximal continuation value from any state (McFadden et al. (1978),Rust (1987)),

$$\bar{V}(X_t,A_t,Y) = \ln\{\sum_{X_{t+1}} \exp(\bar{u}(X_t,X_{t+1},A_t,A^*,Y,\eta) + \beta\bar{V}(X_{t+1},A^*,Y))\} + \lambda$$

where $\lambda \approx 0.577$ is Euler's constant. The conditional choice probabilities take the multinomial logit form,

$$P(X_{t+1}|X_t,A_t,Y) = \frac{\exp(\bar{u}(X_t,X_{t+1},A_t,A^*,Y,\eta) + \bar{V}(X_{t+1},A^*,Y))}{\sum_{X'_{t+1}} \exp(\bar{u}(X_t,X'_{t+1},A_t,A^*,Y,\eta) + \bar{V}(X'_{t+1},A^*,Y))}$$

4 Data, Parameterization and Estimation

This section begins by describing the primary HAMP dataset followed by model parameterization and implementation. Lastly, the estimation procedure and identification is discussed.

4.1 Primary Dataset

The HAMP dataset is publicly available through the US Treasury department as part of the Making Home Affordable Dataset.[15] These dataset contains a record for each its 4.6 million applications. This paper focuses on the 1.1 million participants receiving a permanent HAMP mortgage modification since little data are given on rejected applicants. HAMP data includes mortgage terms prior to and while in HAMP and variables used in the Net Present Value calculation.

Table 1 displays summary statistics on mortgage terms of HAMP participants before and after entry. HAMP reduces the average participant's annual mortgage payments by $9,900, equivalent to a 25

[15]Making Home Affordable is the broader umbrella HAMP is administered and includes the much smaller programs: Homeowner Affordability Unemployment Plan, Homeowner Affordable Foreclosure Alternatives Program, Second Lien Modification Program, and FHA Second Lien Program.

percent increase to annual income.[16] On average, payment reduction is accomplished by a nearly four percentage point reduction in interest rates, extending the mortgage term by four and a half years, and by forbearing 6 percent of the outstanding balance. Across participants significant heterogeneity exists in the housing payment reduction. The 10^{th} percentile had a payment reduction of 18 percent while the 90^{th} percentile had a payments reduction of 67 percent.

Table 2 shows summary statistics of participants upon HAMP entry by June 2013 payment status. Median household annual income is $52,0000, similar to the national median. The average HAMP participant owes 39 percent or $54,000 more on their mortgage than their home is worth with an average home value of $215,200 at the time of modification. On average, exiting participants have higher incomes, lower home values, lower credit scores, are less likely to reside in a housing bust state, and had lower debt-to-income ratios before HAMP participation. Further differnces in HAMP performance across observable characteristics such as modification level, equity, and income are provided in the Appendix Figures 14- 16.

HAMP data do not contain information on second mortgages. which are often present among delinquent households. To capture second mortgages I match HAMP participants to a large mortgage servicing dataset called the Corporate Trust Services (CTS) dataset. The CTS dataset contains mortgage performance data on roughly five million securitized mortgages managed by the Wells Fargo Trustee and is available to investors. The matching procedure uniquely links 18,160 mortgages based on origination mortgage terms, location, and modification timing and terms. Two data restrictions further reduce the sample size to 5,629 observations: modifications occurring after September 2010 and non-missing age information.[17] The modification date restriction is because Zillow housing data, discussed later, is only available beginning in October 2010. Twenty percent of the matched sample report a second mortgage, determined by comparing report the loan-to-value and combined loan-to-value ratios at origination.[18]

Table 3 compares observable characteristics of the matched sample to the comparable full sample split by whether the mortgage is owned by a government-sponsored enterprise (Fannie Mae or Freddie Mac). All CTS mortgages are non-GSE mortgages so unsurprisingly the matched sample appears

[16]Payment reduction calculated assuming delinquent payments recapitalized into mortgage. Not assuming this lowers annual payment reduction to $7,200.

[17]I also restrict the matching procedure to mortgages originated between 2005 and 2007, which comprise 90 percent of the CTS dataset.

[18]If the combined loan-to-value ratio is greater than the loan-to-value ratio, this indicates other liens on the property. The balance and monthly payments on second mortgages are approximated by scaling their balance and monthly payments relative to the primary loan based on the report loan-to-value ratios. As an example, if a mortgage has a $100,000 initial balance with $1,000 monthly payments and reports an 80 percent primary loan-to-value ratio and 100 percent combined loan-to-value ratio, the second mortgage is assumed to have a $25,000 balance with $250 monthly payments.

more similar to the non-GSE sample. Compared to GSE mortgages, non-GSE mortgagees have higher home values, reported incomes, and are more likely to reside in housing bust states than the GSE sample but have quite similar exit rates.

4.2 Parameterization

This section details how model parameters are implemented, either through estimation or chosen from existing literature. Housing market and income process are estimated using secondary data sources including the Panel Survey of Income Dynamics, American Community Survey, Zillow real estate data, and the Case-Shiller and FHFA house price indices. Consumption utility parameters are either estimated from the Consumer Expenditure Survey or taken from Campbell and Cocco (2011). The home attachment distribution, exit shock variance, and systematic mortgage preferences are estimated by solving the dynamic default choice model using HAMP program data.

4.2.1 Homeownership

Local housing costs δ_ℓ are derived from reported real estate taxes, homeowners insurance, and association dues and fees in HAMP data by a procedure detailed in the Appendix. The mean annual housing cost across 259 locations is 2.2 percent of the home value, ranging from 0.8 percent to 4.2 percent.

Housing services H are based on the appraisal value of the home provided in the HAMP dataset adjusted by rental price levels and housing costs. For a home appraised at value $p_t(H,\ell)$, H is determined using the purchase price equation (3):

$$H = \frac{p_t(H,\ell)(1-\beta(1+\nu_{\ell,t}))(1+\delta_\ell)}{R_{\ell,t}}$$

The home sales cost s is assumed six percent of the purchase price following standard real estate agent fees.

4.2.2 Income

Household income is central to the HAMP mortgage modification process since modified housing payments must be 31 percent of current income. HAMP data include the monthly income used for calculating the mortgage modification.[19] This income is used for the initial income level of each household.

Income shocks are important in the model because they can induce liquidity constraints, forcing households without precautionary savings to exit the home. More volatile income streams increase the propensity for households to self-insure against transitory income shocks. Large income shocks can put pressure on households to re-optimize their housing budget share, altering the value of moving to the rental market.

HAMP data contains no dynamic income information. To update expected household income each period, I estimate the exogenous household income process in Equation (1). This process is estimated separately by age category using the bi-annual 2001 through 2009 waves of the Panel Survey of Income Dynamics.[20] The income process consists of three parameters: the mean growth rate, μ_{κ}^{ι}, the variance of the income shock, σ_{κ}, and the mean-reversion parameter, ρ^{iota}. Estimating separate income processes by age allows the model to capture the higher expected growth rate and variance of income among younger households compared to the more stable and eventually declining expected income among elderly households. Estimation results of the twelve income parameters are listed in the Income section of Table 4.

Local income shock observations $\omega_{\ell,t}$ come from the 2009 through 2014 American Community Surveys. These shocks are measured as the percentage change in median household income for each location. Local income shocks are used to update the expected income distribution for each household in the likelihood function calculation.

Progressive federal income tax rates reduce discretionary income across income levels among HAMP participants. To approximate the share of income paid by households in taxes after accounting for deductions and tax credits, I use the effective income tax rates reported for each income quintile by the Tax Policy Center in 2009. These tax rates vary from 1 percent for the lowest quintile to 23.2 percent for the highest quintile.

[19] Participants must report their income, including wages, salary and bonuses, benefit income including unemployment and social security, rental income, and self-employment income along with an either their tax return from the previous year or an IRS form 4506-T or 4506T-EZ which allows the lender to receive tax information from the IRS on the borrower. Lenders must verify all reported income, in particular by looking at recent pay stubs.

[20] Both Campbell and Cocco (2011) and Laufer (2011) use a similar procedure to estimate the income process.

4.2.3 Other Debt Obligations

Other debt obligations D are reported by HAMP participants. Program documentation states these obligations include payments on revolving credit payments (i.e. credit cards) and installment debts such as student loans, car loans or leases, mortgage insurance premiums, second mortgages or second home mortgage payments.[21] On average, HAMP participants report paying 25 percent of income to other debt obligations.[22] Renters with debt obligations greater than income and assets are provided with housing $\bar{H} = \underline{h}$ equal to the minimum housing level, and $\bar{C}$ equivalent to \$300 of consumption in the initial period.

4.2.4 Assets

Assets are important in the default model for consumption smoothing and insurance against income shocks. HAMP data do not provide liquid asset holdings of households. Following Gregory (2011), in place of observed assets I substitute an expected initial asset distribution for each household. Future assets then become a latent variable in the model, determined by other state variables. The key to this technique is finding a dataset that reports assets on a comparable group of households.

To approximate initial asset holdings of HAMP participants I use the 2010 Survey of Consumer Finances, a tri-annual survey of US wealth. I restrict the sample to the 215 households responding affirmative to being 60 days or behind on any debt payments within the past year.[23] The initial asset holdings distribution $\hat{Q}^{\iota}(p_a)$ is calculated relative to income and separately by age categories. The initial asset assignment procedure is detailed in the Appendix.

Since initial assets are unobserved, I condition the likelihood function by computing likelihoods with respect to the auxiliary estimate of each household's distribution of initial asset holdings $\hat{Q}^{\iota}(a)$. For a given initial asset value of A_{i0}, I compute the model's implied latent asset path consistent with a

[21] Installment debts must have more than ten months of payments remaining to qualify.

[22] In the model, other debt obligations are meant to represent required, pre-existing debts where no consumption value is gained from their payment. Ideally I would throw out consumption-related debts such as car lease payments and credit cards, while keeping student and car loans. However, HAMP data do not differentiate between these types of debt. To compromise, I discount other debt obligations by 50 percent and cap other debt obligations at ten percent of initial income after subtracting off second mortgage payments, which I observe in the matched dataset.

[23] Data on households wealth of delinquent homeowners is scarce in general. For example, the 2007 SCF contains only 78 households which both own a home and report being 60 days behind on any debt payments within the past year. Other large national surveys which contain wealth information, such as the PSID and NLSY both provide fewer than 100 observations of these households.

household's observed choice sequence using,

$$\begin{aligned}\hat{A}_i(t|\{X_{it}\},A_0,Y,\theta) &= A_{i0} && \text{if } t=1\\ \hat{A}_i(t|\{X_{it}\},A_0,Y,\theta) &= A^*(X_{it},X_{it-1},A_{it-1},Y) && \text{if } t>1\end{aligned}$$

where X_{it} represents the state vector, Y is individual-level heterogeneity, and A^* is the optimal asset choice function defined in equation (6).

4.2.5 Housing Market

Local housing markets are characterized by the rental price per unit of housing $R_{\ell,t}$ and the price-to-rent ratio $\psi_{\ell,t}$. Initial rental price levels are based on housing budget shares reported in the 2010 American Community survey. Full details on initial price level determination are provided in the Appendix.

Price-to-rent ratios are observed from data provided by Zillow.[24] This data are available monthly for 209 metro locations and 50 states beginning in October 2010 through June 2014. Expected rental price growth rates $\nu_{\ell,t}$ are derived from $\psi_{\ell,t}$ by manipulating equation (4):

$$\nu_{\ell,t} = \frac{1}{\beta} - 1 - \frac{1}{\beta(1+\frac{\delta_\ell}{1-\beta})\psi_{\ell,t}}$$

The distribution of price-to-rent ratio shocks, $\zeta_{\ell,t}$ are assumed distributed $N(0,\sigma_\zeta)$. Based on Zillow data during this time period, the variance of these shocks is $\sigma_\zeta = 0.0628$.

Random rental price level shocks $\varepsilon_{\ell,t}$ are observed by combining house price indices and rent-to-price ratios. When available the Case-Shiller index is used to track price shocks, otherwise the Federal Housing Finance Authority house price index is used to track house price changes.[25] Rental price shocks $\varepsilon_{\ell,t}$ are determined by differencing the purchase price levels and using equation (3). The log price level shocks $\varepsilon_{\ell,t}$ are assumed drawn from a mean-zero normal distribution with variance σ_ε. The variance of log rental price level shocks observed between October 2010 and June 2014 is 9.924e-4.[26]

[24] Zillow data is publicly available at `http://www.zillow.com/blog/research/data/`

[25] The Case-Shiller Tiered Index is used in the 16 MSAs for which it is available. This monthly index splits each MSA into three tiers based on home value and tracks house price changes in each tier. Separating tiers can capture intra-MSA variation in house prices. The Federal Housing Finance Authority all-transaction house price index is used to update other location price levels. Monthly values are imputed linearly between quarters.

[26] It is likely that both σ_ε and σ_{zeta} are estimated too high as this time period experienced quite high volatility in the housing market relative to historical standards. Given this is the only period for which I have both price level and rent-to-

4.2.6 Utility Parameters

Nine parameters govern periodic household consumption utility. These include the relative weight of housing Θ, coefficient of relative risk aversion γ, minimum housing consumption $\underline{h}$, scaling parameter for exit shocks α, bequest motive b, mean μ_ξ and variance σ_ξ of the permanent home attachment distribution, and systematic preference parameters ρ_1, ρ_2 which relate to the effective mortgage rate and credit risk factor respectively.

The relative weight of housing Θ and the minimum level of housing consumption $\underline{h}$ are estimated using the elasticity of housing budget shares to income observed in the 2010 and 2011 Consumer Expenditure Surveys. Regressing housing budget shares on income among renter households identifies these parameters as outlined by Eeckhout et al. (2010).[27]

Exit preference shocks $\eta_t(D)$ are assumed drawn from a Type-I extreme value distribution. The variance of these shocks are normalized by α that scales them relative to periodic consumption, and is estimated using HAMP performance data.

Households draw their permanent attachment value ξ_i from the distribution G_ξ, assumed to be normally distributed with a mean μ_ξ and variance σ_ξ. I approximate this distribution with three equally spaced support points, as suggested by Kennan (2006). The mean and variance are estimated using HAMP performance data.

The preference parameters ρ_1 and ρ_2 capture systematic household rental market preferences Z_i of the effective mortgage rate and credit risk factor of the household respectively. The effective mortgage rate R^{eff} approximates the interest rate on the full mortgage balance as an average of the primary interest rate R^M and 0, weighted by the level of principal forbearance: $R^{\text{eff}} = R^M(1 - F^M)$. The credit risk factor is observed as the FICO score in the HAMP data.

The coefficient of relative risk aversion γ, and bequest motive b are not identified from model estimation. Following Campbell and Cocco (2011), I set $\gamma = 2$ and $b = 400$.

4.2.7 Other Parameters

I set the annual discount rate $\beta = 0.94$. This is slightly lower with standard literature values that typically range between $0.95 - 0.97$. I opt for a lower value because of the role of the discount factor

price data, I can not expand the pool of observations to estimate these parameters.

[27]Eeckhout et al. (2010) identify similar parameters but in a Stone-Geary utility function.

in the housing purchase price equation (3) as the expected growth rate is bounded by $1-\beta$. Historical nominal US house price growth is 3.5 percent annually. Choosing $\beta = 0.94$ provides a larger range of expected rental price growth rates, with a maximum value of six percent. The annual interest rate r^f is set to three percent consistent with the 30-Year treasury rate. The annual inflation rate π is set to two percent following recent trends.

4.3 Estimation

The mortgage default model consists of 22 parameters: 9 utility parameters, 4 housing market parameters, 6 income process parameters, and 3 other time-related parameters. Here I describe my estimation procedure and sketch an outline of identification of estimated parameters.

4.3.1 Default Model Estimation

To estimate the parameter-vector θ, assume a sample of households $i = 1,\dots,N$ solve the previously stated dynamic programming problem. Households vary by their endowed property H, mortgages M_1 and M_2, other debt obligations D, initial income I_0, location ℓ, credit and mortgage characteristics Z_i, and age ι. Each household begins with initial assets drawn from $\hat{Q}^{\iota}(p_a)$. For each location ℓ I observe an initial rental price level $R_{\ell,t}$, housing cost δ_ℓ, series of price level shocks $\{\varepsilon_{\ell,t}\}$, price-to-rent ratios $\{\psi_{\ell,t}\}$, and income shocks $\{\omega_{\ell,t}\}$. For each household I observe a string of mortgage payment choices $\{D_t\}_{t=1}^{t^i_{end}}$, where $D_t \in \{\text{pay,exit}\}$.

The Bellman equation is solved recursively by discretizing state space for income, assets, house price level, and the price-to-rent ratio based on initial values. Observed data are linearly imputed across discrete states. Income, house price level, and price-to-rent ratio states are scaled relative to initial values for each household and location, and asset states are scaled relative to initial household income. I use nine state points to approximate $R_{\ell,t}$, five points for ψ, five points for I, thirty asset states, and solve over seven years or 84 time periods for a total of 567,000 states.

Conditional on an initial assets the time t likelihood for household i is:

$$l_{i,t}(\theta|X_{i,t},Y,A_0) = \sum_{X_{i,t-1}} Pr(X_{i,t}|X_{i,t-1},Y,A_0)Pr(X_{i,t-1})$$

The expected income distribution in $X_{i,t}$ is updated each period conditional on previous payment choices:

$$Pr(X_{i,t}) = \frac{\sum_{X_{i,t-1}} Pr(D_{t-1} = \text{pay}|X_{i,t-1}) Pr(X_{i,t}|X_{i,t-1}, Y, A_0) Pr(X_{i,t-1})}{\sum_{X_{i,t-1}} Pr(X_{i,t}|X_{i,t-1}, Y, A_0) Pr(X_{i,t-1})}$$

That is, expected current income conditions on the likelihood of prior period payment choices.

Households are observed from $t = 1, \ldots, t^{exit}$. The total conditional household likelihood for a string of mortgage payment decisions is:

$$l_i(\theta|X_{i,t}, Y, A_0, \xi_{i,j}) = \Pi_{t=1}^{t^{exit}} \sum_{X_{i,t-1}} Pr(X_{i,t}|X_{i,t-1}, Y, A_0) Pr(X_{i,t-1})$$

The household's unconditional likelihood contribution is obtained by integrating this conditional expression with respect to the distribution of the initial assets Q^{ι} and home attachment G_{ξ}:

$$\hat{l}_i(\theta|\{X_{i,t}\}_{t=1}^{t^{exit}}, Y) = \int\int l_i(\theta|\{X_{i,t}\}_{t=1}^{t^{exit}}, A_0) dQ^{\iota}(p_a) dG_{\xi}(\xi;\theta) \tag{7}$$

Given preference types $j = 1, \ldots, J$ and asset states $a = 1, \ldots, A$ the integral in equation (7) is approximated by:

$$\hat{l}_i(\theta|\{X_{i,t}\}_{t=1}^{t^{exit}}, Y) = \sum_{p_j=1}^{J} \sum_{p_a=1}^{A} l_i(\theta|\{X_{i,t}\}_{t=1}^{t^{exit}}, Y_{i,j}, A_{i,0} = Q^{\iota^{-1}}(p_a), \xi = G_{\xi}^{-1}(p_j))$$

The log-likelihood of the full sample of N households is the log of the product of the individual household likelihoods:

$$L(\theta) = \log(\Pi_{i=1}^{N} \hat{l}_i(\theta|\{X_{it}\}_{t=1}^{t^{exit}}, Y_i) \tag{8}$$

The log-likelihood is maximized for the parameter vector θ using a version of Newton's algorithm.

4.3.2 Identification

Below I sketch an outline of the variation in data needed to identify model parameters.

The mean of unobserved permanent home attachment μ_{ξ}, is identified by the estimation sample default rate. The mean μ_{ξ} adjusts the average utility distance between remaining in the home and exiting to the rental market to fit the observed rate at which households exit their home. Empirically, μ_{ξ} captures all permanent unobserved heterogeneity between households. Additionally, μ_{ξ} will also incorporate any model misspecification which influences the relative benefit of homeownership versus renting.

The variance of the home attachment distribution σ_ξ is identified through the persistence of choices made by households. If previous decisions are highly correlated with future decisions, independent of the state, σ_ξ will be high. While I argue ξ is primarily represented by home attachment, households heterogeneity in other factors such as the preference for owning versus renting, aversion to default, or discount rates would be captured in estimating σ_ξ.

The scaling parameter α, which relates the variance of the exit shocks $\eta_t(D)$ to periodic consumption is identified by the responsiveness of households to exit their home in response to variation across individuals in mortgage value and income tax rates, and over time in response to geographic income shocks and house price shocks. Higher α values suggest a diminished role of random forces driving the default decision, while lower α values suggest default occurs relatively randomly. The size of preference shocks $\eta_t(D)$ relative to average home attachment μ_ξ relates the importance of random as opposed to permanent unobserved heterogeneity across households.

Parameters corresponding to systematic preferences for homeownership ρ_1 and ρ_2 are linearly related to the effective mortgage rate and credit risk respectively. These parameters are identified by the default rate dispersion across these dimensions not otherwise accounted for by observed characteristics.

5 Parameter Estimates and Model Fit

Table 4 presents estimates of the model's structural parameters using HAMP performance data. I estimate the variance of exit preference shocks η to be 8.8 times average monthly consumption utility. This can be difficult to interpret directly. For comparison, average periodic utility is around 0.03 utils so a standard deviation increase in an exit shock is equivalent to a 0.035 standard deviation increase in a permanent home attachment draw ξ over the course a year. This implies the impact of permanent home attachment dwarfs the impact of random exit shocks.

I estimate average home attachment μ_ξ to be 0.1843 utils per period, or around 2.5 times its standard deviation. This large value reflects a strong household preference on average to remain in the endowed home, valuing the home at 70 percent of periodic consumption. The size of permanent attachment compared to random shocks is consistent with migration literature that find large moving costs or location attachment. The high estimated mean attachment implies households solving the default model would largely prefer the rental market in the absence of attachment. This result must be interpreted with some caution as it incorporates many assumptions about housing rental and ownership markets. For example, the exclusion of rental market frictions such as moving costs or administrative overhead costs increase the estimated size of mean home attachment.

The heterogeneity of home attachment σ_ξ is less subject to model uncertainty since it is identified from the persistence of mortgage payment choices over time. A standard deviation increase in home attachment for a single period is equivalent to 27 percent of periodic consumption. As home attachment is permanent, a standard deviation decrease in the initial draw of home attachment significantly decreases the incentive to remain in the home, increasing the expected annual default rate from 10 percent to 32 percent for the average HAMP participant.

The other estimated parameters related to systematic preferences ρ are directly comparable to each other. A one percentage point increase in the effective interest rate is equivalent to a 71 point decline in credit score. In relation to home attachment a one percentage point increase in the effective interest rate is equivalent to 25 percent of a standard deviation decrease home attachment draw.

Table 5 compares model simulations using estimated parameters to observed default rates across a variety of observable dimensions. Simulations using the matched CTS estimation sample use state transition probabilities calculated given the estimated parameter vector. This means simulations are essentially drawn infinity times. Simulations generate a marginally lower default rate by 0.25 percentage points from a base of 17.77 percent. Breaking down default rates by observable categories, the average absolute difference between simulated and observed default rates is 1.5 percentage points with largest discrepancies among participants with positive home equity, high interest rates, and those beginning their modification in the first half of 2011.

Figure 3 compares the default hazard rate over time between the simulations, the estimation sample of matched CTS participants, and the full non-GSE sample. Simulations follow the general decreasing trend over time displayed among the estimation sample. Periodic default volatility in the estimation sample is not observed in simulated data due to the small estimation sample size. This is reflected in the smooth hazard rate among all non-GSE participants, though an odd feature of the full non-GSE hazard function is the hill shaped default distribution over the first 6-8 months after modification. This shape does not appear in the estimation sample or simulations, but may reflect an initial enthusiasm factor to remain in the program.

I additionally compare observed and simulated default rates across a number of other dimensions including modification level, equity, income and vintage year. Default hazard rate patterns match well for these categories, although later time periods match less well among high interest rate or high income. These simulations are displayed in Appendix Figures 17- 20.

Figure 4 compares observed and simulated default rates by location. Simulations are not able to match the dispersion between locations in default rates. Extreme values of default rates in simulations differ by six percentage points while observed default rates differ by twenty percentage points. Simulations are able to reasonably match the relative default rate ordering of locations as the correlation between simulated and observed default rates is 0.422.

6 Policy Simulations

I use the estimated parameters to investigate mortgage defaults of HAMP participants under counterfactual policy scenarios. I begin by considering the scenario in which HAMP does not exist, creating a benchmark to measure the success of the program against. HAMP benefits are quantified by the number of defaults prevented as of June 2013 as well as over a five year period. To evaluate HAMP I calculate the program cost per prevented default. Counterfactual policies measure default responses to changes in the HAMP target payment amount. Fitting the simulated cost per prevented default as a function of the target payment level gives the optimal program target payment level as a function of the social cost of foreclosure.

6.1 Cost-Benefit Analysis of HAMP

In order to determine how many defaults HAMP prevented, one must speculate about the world in its absence. As a national program with few restrictive eligibility criteria, an credible control group is not readily available to view market forces in HAMP's absence. One theory is that all HAMP participants would be foreclosed on without the program, since most were delinquent on mortgage payments upon HAMP entry. However between 2009 and 2013 lenders modified many delinquent mortgages and it is likely many HAMP participants would have sought similar modifications.[28] Historically, private mortgage modifications have been far less generous than the HAMP modification. Often private modifications merely recapitalize outstanding arrears into the mortgage balance and cure the loan (Quercia et al., 2009).[29] My benchmark specification assumes all HAMP participants receive this minimal mortgage modification is the absence of the program.

[28] Private lender modifications represent about 80 percent of all mortgage modifications between 2010 and 2013.

[29] Arrears refers to overdue debt payments. To cure a loan means to make a delinquent borrower current.

6.1.1 Costs

Simulation results using the HAMP compensation structure shown in Table 6 calculate current HAMP costs at $9.5 billion with expected five year costs of $20.8 billion. A "best case" scenario, which assumes all participants still making payments will continue to do so, would push costs up to $22.6 billion. The majority of these costs arise from the HAMP payment reduction subsidy as opposed to the lump-sum and good-performance payments.[30] My estimated costs are larger than current reported HAMP costs of $6.5 billion because HAMP does make direct payments to GSE entities, however I assume an implicit transfer is made to these entities.[31] The assumption of implicit payments seems reasonable given Freddie Mac and Fannie Mae received $150 billion in assistance from the federal government during this time period.

Several other factors must be considered when interpreting the $21 billion HAMP price tag. One factor is the deadweight loss associated with the government raising the money to fund HAMP. Ballard et al. (1985) finds the deadweight loss of an additional $1 of income tax revenue to be around $1.30 would imply a true HAMP cost of $29 billion. Another less quantifiable factor is the cost associated with submitting and processing the nearly 3 million rejected or non-official HAMP modifications. HAMP required a significant amount of paperwork and effort from both applicants and lenders such as documenting and verifying income and appraising the home. Lastly, there may be concern of the moral hazard HAMP creates. Those concerned with the lax lending and over-indebtedness prior to the housing bust worry programs such as HAMP encourage similar future behavior. However, others argue that circumstances surrounding HAMP's creation were extreme enough that it could be credibly seen as a one-time or very rare event that will not affect behavior.

6.1.2 Benefits

The primary goal of HAMP is to prevent defaults. Table 6 presents simulation results of HAMP defaults compared to the baseline scenario in three cases. One case is as of June 2013 and the other two are five year projections: a best case scenario and an expectation calculated from current exit rates.[32] Simulation results find HAMP has prevented 515,354 defaults as of June 2013 and over a five year period expects to prevent 505,803 defaults relative to the baseline specification.

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[30] Full details of my approximation of the HAMP cost structure are provided in the Appendix. Expected future costs do no include potential future participants. The HAMP application deadline was recently extended to December 2015.

[31] The daily TARP update which tracks HAMP payments can be found at `http://www.treasury.gov/initiatives/financial-stability/reports/Pages/default.aspx`

[32] Five year projections reference an applicant's modification date as opposed to HAMP existence. Five years is chosen because that is when HAMP ceases subsidy payments.

Translating the benefit of a prevented default into dollar terms is not an easy task. The most commonly studied foreclosure externality is its effect on local property values. Campbell et al. (2009) and Harding et al. (2009) estimate each foreclosure lowers nearby home values by one percent, with Campbell et al. (2009) restricting this to homes within 0.05 miles of the foreclosed property. My preferred back-of-the-envelope calculation of the social benefit of a prevented foreclosure is \$16,000.[33] Using this estimate, I find HAMP expects to generate \$8 billion of social value through preventing 505,803 defaults.

While preventing defaults is the primary focus of HAMP, delaying default may also provide benefits, though I am aware of no empirical estimate of this effect. If foreclosure externality costs are non-linear, notable in relation to its effect on property values, the clustering of foreclosures may amplify their negative effects. Non-linear negative externalities imply that smoothing a foreclosure spike, such as the one observed following the 2008 housing bust, may be particularly beneficial. Figure 5 displays the simulated distribution of defaults over time between HAMP and the baseline specification. Many prevented defaults from HAMP occur in the initial periods and on average among defaulters HAMP delays default by six months.

Aside from directly prevented defaults, HAMP may also indirectly prevent defaults by keeping house values from dropping. If households default because their home value drops then a prevented default may prevent nearby homes from foreclosing given the observed property value declines after foreclosures. My back-of-the-envelope calculations suggest this is a small effect though, with each prevented default in HAMP preventing an additional 0.04 defaults or a total of 20,600 additional prevented defaults. I compute this using the one percent home price decline from foreclosure found in Campbell et al. (2009) and using data from Freddie Mac to estimate both a two-year likelihood of default conditional on equity combined with the current distribution of equity among homeowners.

HAMP provides a direct benefit to both participating lenders and households through subsidizing the mortgage modification process. According to the HAMP NPV calculation, the average HAMP modification provides the lender with about \$5,000 in benefit, so in total around \$5 billion of program

[33] This calculation assumes a foreclosure affects fifteen homes at an average home value of \$215,000 yields a \$32,250 benefit for each prevented foreclosure on local property values. It is unclear whether this observed property value loss is a true externality. The house price decline could be true property value loss which could stem from increased criminal activity in vacant homes or poor maintenance during foreclosure. However, the observed price decline may be attributed to the negative price pressure a forced sale puts on the housing market, leaving its net social cost at zero. Anenberg and Kung (2012) investigate this issue and attribute the bulk this externality to price pressure instead of property value loss. Other foreclosure costs come from local government money spent processing the foreclosure and potentially demolishing the home. Apgar and Duda (2005) report foreclosure costs to local governments ranges between \$430 to \$34,199 depending on property condition. My preferred estimate discounts the price decline externality by two-thirds and assumes most foreclosed properties are not demolished, yielding a social benefit to a prevented default at \$16,000.

expenditures is a direct payment to lenders. Participating households save on mortgage payments, worth at least $13 billion based on the average payment reduction and the number of payments made in the absence of the program. From a social planner perspective this may represent a suboptimal redistribution as the beneficiaries, stockholders and homeowners, are likely to be wealthier than the average household.

The success or failure of HAMP depends on how one interprets the previous discussion on the program costs and benefits. At most I find HAMP generates around $8 billion of social benefit from preventing foreclosures. Using only observed program costs, HAMP will pay $21 billion or $41,096 per prevented default. Comparing this solely to the externality benefits implies an overall program loss of $13 billion. Factoring directly transfers to lenders and participants brings HAMP closer to revenue neutrality, though the deadweight loss of taxation pulls HAMP back towards a large loss. However, those convinced that prevented defaults are worth substantially more than $16,000 or that clustering of foreclosures is particularly bad may find HAMP to be a bargain.

6.2 Alternative Target Payment Levels

The central feature of HAMP is reducing monthly housing payments to 31 percent of monthly income. A natural question is how alternative target payment ratios change program results.[34] If the main cause of default is liquidity constraints, higher target payment levels may have continued to relieve this constraint while reducing costs. If defaults are more responsive to mortgage value or 31 percent did not adequately relieve liquidity constraints, reducing the target payment level may increase program cost effectiveness. I simulate two counterfactual policies: one, raising the target payment level to 38 percent and the other lowering the payment level to 25 percent. The optimal target payment level as a function of foreclosure costs is then mapped using results.

To simulate counterfactual policies, I must make assumptions about program participation, cost structure, and modification process. When raising the target payment level I assume all current program participants continue to participate if their prior payment to income ratio is at or above the target level. When lowering the target payment level, I assume all current participants remain in the program and no additional participants are added. In effect this assumes program benefits increase but eligibility requirements remains unchanged. The cost structure of counterfactual policies mimic the current structure, differing only on the payment reduction subsidy range. When raising the target payment level, I continue to assume servicers receive a 50 percent subsidy for payment reductions,

[34] The 31 percent target payment ratio used in HAMP was not derived from any optimal policy calculation but is based of historical housing budget share levels.

maxing out at a seven percentage point reduction in payments.[35] When lowering the payment-to-income ratio, I assume servicers receive an additional 50 percent subsidy for the extra payment reduction on top of current compensation. The counterfactual modification process replicates the current process detailed in the Appendix except eliminates the 30 percent maximum forbearance restriction when lowering the target payment level. Finally, I allow participants to remain in the program even if the maximum modification does not reach the target payment level.[36]

Table 6 presents program costs and defaults of counterfactual target payment level policy simulations. Raising the target payment level to 38 percent increases June 2013 defaults by 99,768 and expected five year defaults by 141,075. This lowers expected program costs by 45 percent and cost per prevented default by 23 percent. Decreasing the target payment level to 25 percent prevents an additional 46,471 defaults by June 2013 and expected five year defaults by 89,032 while increasing program costs and cost per prevented default by 29 and 52 percent respectively. Figure 7 plots the cost-effectiveness of these counterfactual proposals relative to the current target level of 31 percent. Fitting the cost per prevented default as a quadratic function of target payment level suggests a target payment level of 52 percent is needed for program costs to cover the $16,000 social benefit of a prevented foreclosure.[37] Only a quarter of current HAMP participants would be eligible for modification under a 52 percent target payment level policy.

Figure 6 displays the distribution of defaults over time under counterfactual policy simulations. In general the distribution of counterfactual policy simulations are quite similar to HAMP differing more the level of defaults as opposed their timing. This indicates welfare losses related to delaying default or easing initial liquidity constraints are minimal when increasing the target payment level to 38 percent (or similarly gains are minimal in reducing the target payment level).

7 Conclusion

This paper analyzed the Homeowner Affordability Modification Program and finds it prevented 515,354 defaults as of June 2013 and prevents 505,803 over a five year period relative to a baseline modification program where participants received no payment reduction. Each prevented default costs

[35] This implies servicers receive no additional compensation for reducing payments to the 45 percent payment-to-income ratio, only for the reduction from 45 to 38 percent.

[36] This occurs when taxes, insurance, and association dues alone are greater than the target payment level. Only 1.4 percent of participants hit this threshold in the 25 percent target level policy.

[37] Note that the 52 percent target payment level is outside the range of simulated policies, reducing its credibility of predicting defaults.

$41,096, significantly above its societal benefit of $16,000 projecting total program losses of $12.7 billion. A counterfactual proposal increasing the target payment level of the program to 38 percent increases defaults by 141,075, but reduces costs by $9.2 billion lowering the cost per prevented default to $31,606.

Earlier work by Agarwal et al. (2017) found HAMP reduced foreclosure rates by 12 percent. Using back-of-the envelope calculations this paper suggests an upper bound on the foreclosures rate reduction at 7.5 percent between 2010 and 2013, bounded by the transition of prevented defaults to prevented foreclosures.[38] This lowers the estimated direct impact of HAMP, but should be noted that Agarwal et al. (2017) allows HAMP to influence debt renegotiation outside of HAMP.

To analyze HAMP, I developed and estimated a structural household mortgage default model. Focusing on HAMP participants gives the unique combination of detailed household financial information, systematic mortgage assignment, and large sample size, allowing for a comprehensive accounting of the household problem while still obtaining precise parameter estimates. Important empirical contributions of the paper include estimating the distribution of home attachment among HAMP participants and the degree of randomness in exiting the home. Estimated home attachment and exit shock variance imply variation across households in permanent attachment contributes more to default than variation across time within households in preference to leave the home. A one standard deviation increase in an exit shock is equivalent to a 0.42 standard deviation decrease in one period of home attachment.

Continuing to gain an understanding of the dynamics of mortgage default is important for future policy and lender responses to mortgage default. Future work could build upon this by incorporating the option to re-enter the ownership market after initial exit, including a refinancing or home equity option, and more accurately tracking income and asset flows of these households. Additionally, identifying whether a social or psychological "default cost" exists, as proposed in Guiso et al. (2009), could be an important improvement for future work, as the model currently assumes a ruthless homeowner is making the decision to sell or default on the house upon exit.

Future program iterations could increase its cost-effectiveness by raising target payment levels. Restructuring the modification procedure to trade lower initial housing payments for increasing the temporary aspect of assistance may provide additional cost-effectiveness. Currently, the reduced mortgage payments made after the home has regained positive equity, which can occur for decades after modification, appear inefficient as the household is no longer a default threat. Solving for the optimal modification procedure remains an interesting question for future research.

[38] This calculation is based on extrapolating newly initiated foreclosures reported in the OCC mortgage metrics reports.

HAMP was created in a moment of panic, trying to avoid a complete financial meltdown. Millions of homeowners still remain in homes worth far less than they owe on their mortgage and presumably contemplate whether to continue paying or walk away. HAMP provides evidence that large adjustments to mortgage terms can delay mortgage exit significantly, however the profitability of such modifications remains unclear. This paper used program results to measure the responsiveness of households to exit their home in relation to their mortgage value to estimate defaults prevented under alternative scenarios and uncover the distribution of unobserved contributing factors to default. The extent HAMP contributed to preventing a worst-case financial outcome is an open research question. If HAMP's contribution is found to be significant, that benefit may far outweigh HAMP's $20.8 billion price tag.

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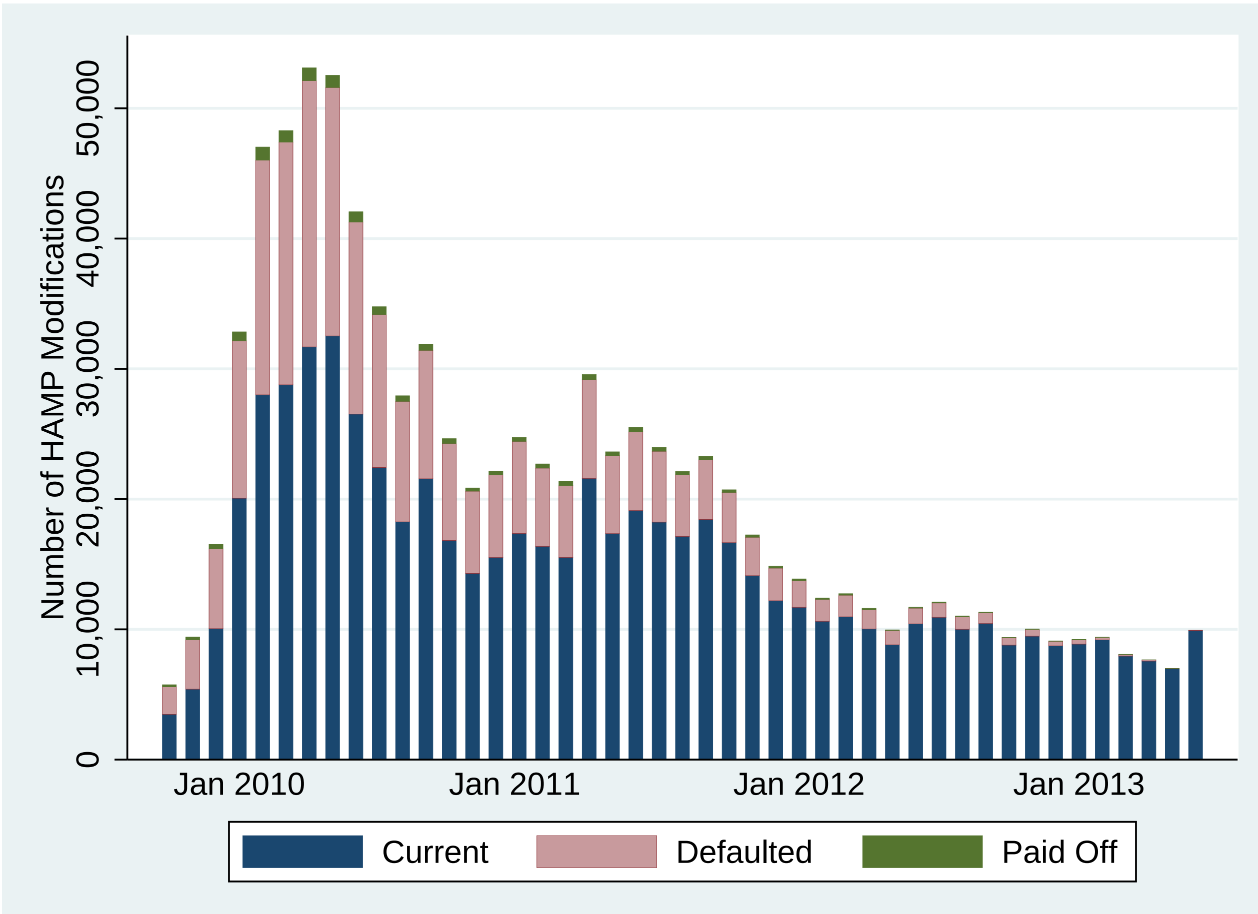
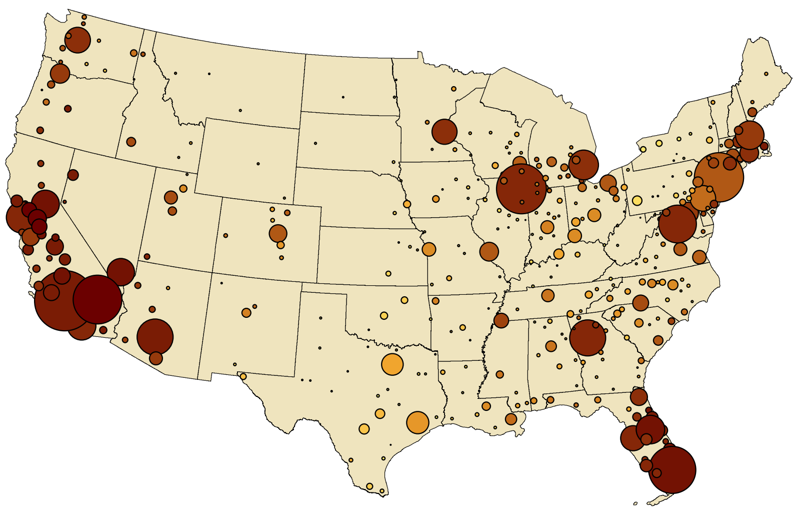
Tables and Figures

Figure 1: HAMP Modification Vintage Month, by June 2013 Payment Status



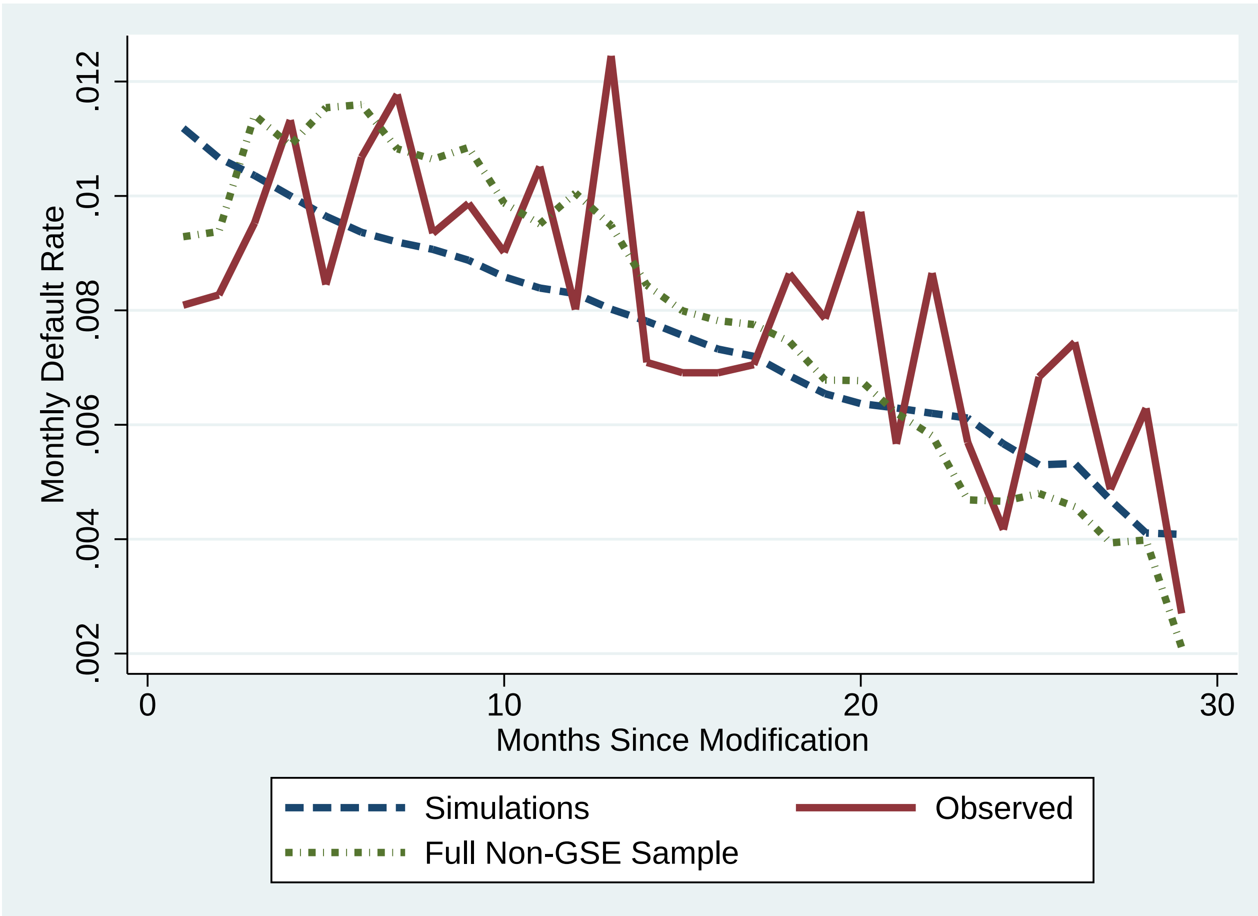
Notes: This figure presents the number of HAMP participants by month of official modification date. Bar color represents HAMP status as of June 2013. Current means mortgage is still active, Defaulted means mortgage became 90 days delinquent, and paid off means the mortgage balance has been paid off.
Source: Making Home Affordable program dataset.

Figure 2: HAMP Participation Level and Intensity by MSA



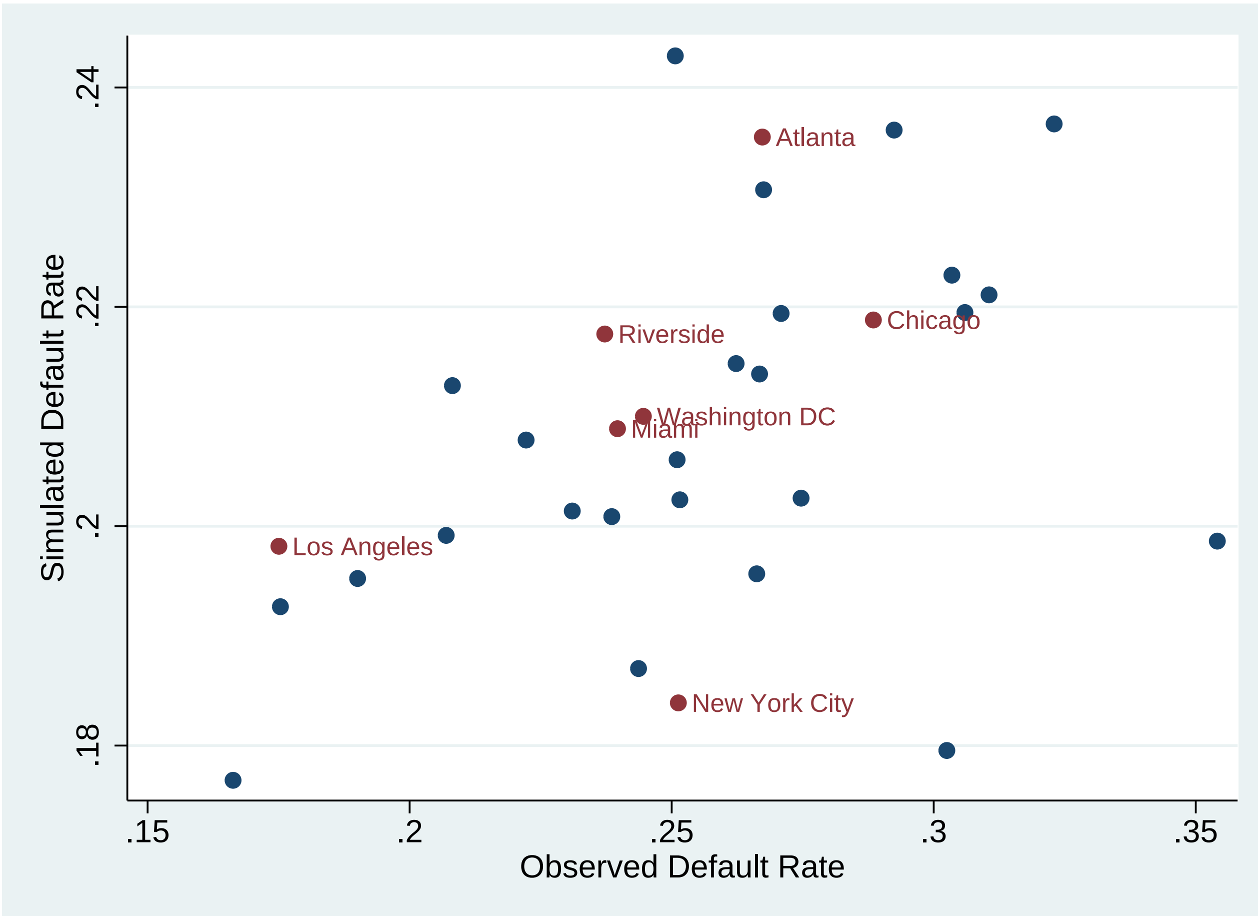
Notes: This figure represents the number and rate of HAMP participation by MSA. Bubble size proportional to the log of the number of participants. Bubble color reflects the rate of participation as a fraction of the MSA population, with darker bubbles representing higher participation rates.
Source: Making Home Affordable program dataset.

Figure 3: Simulated vs. Observed Periodic Default Rate, by Months Since Modification



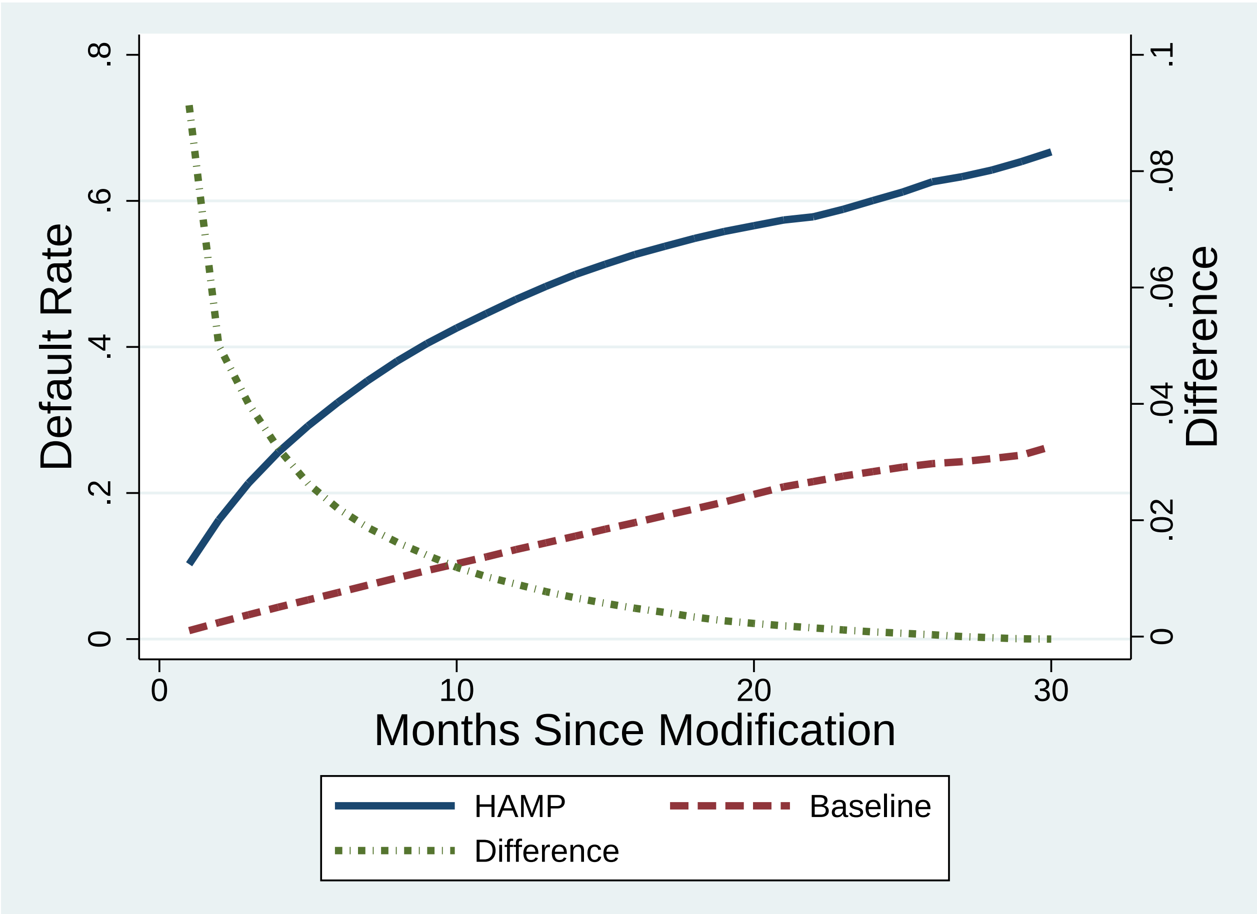
Notes: This figure displays the monthly default rate of HAMP participants as a function of months since official modification began. Simulated and Observed data are calculated using the matched CTS subsample. The Full Non-GSE Sample uses all HAMP participants with mortgages not owned by a GSE enterprise, from which the CTS subsample is matched upon. Simulations use estimated parameter values and computed transition probabilities to determine monthly default rate.
Source: Making Home Affordable program dataset, matched CTS subsample.

Figure 4: Scatterplot of Simulated vs. Observed Default Rates, by MSA



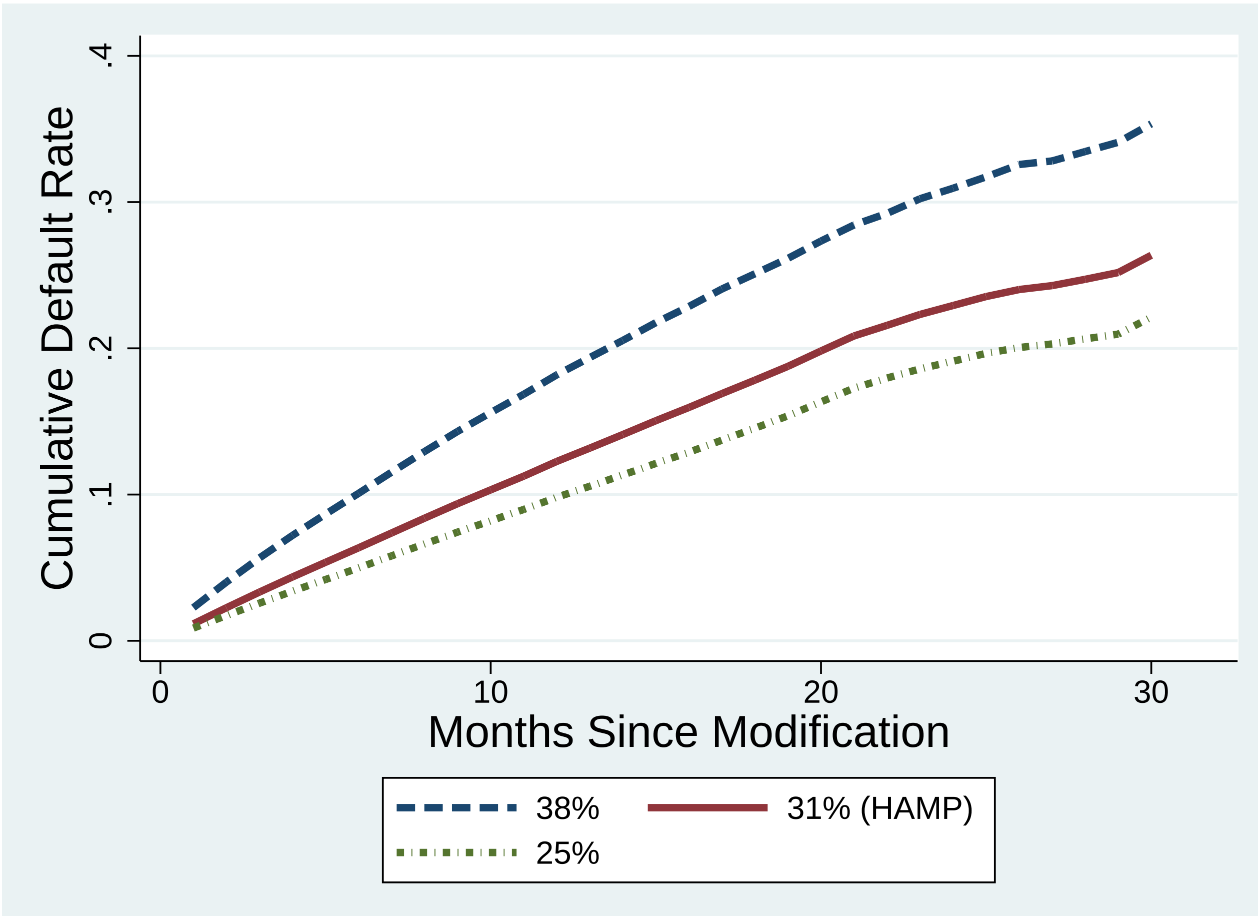
Notes: This figure displays simulated versus observed June 2013 default rates by MSA. Observed default rates taken from Full Non-GSE HAMP sample. Simulations use estimated parameter values and computed transition probabilities to determine default rate among CTS matched subsample. Note that simulations systematically under-predict default rates here due to over-prediction of loans paid off.
Source: Making Home Affordable program dataset.

Figure 5: Cumulative Default Rates: HAMP versus Baseline



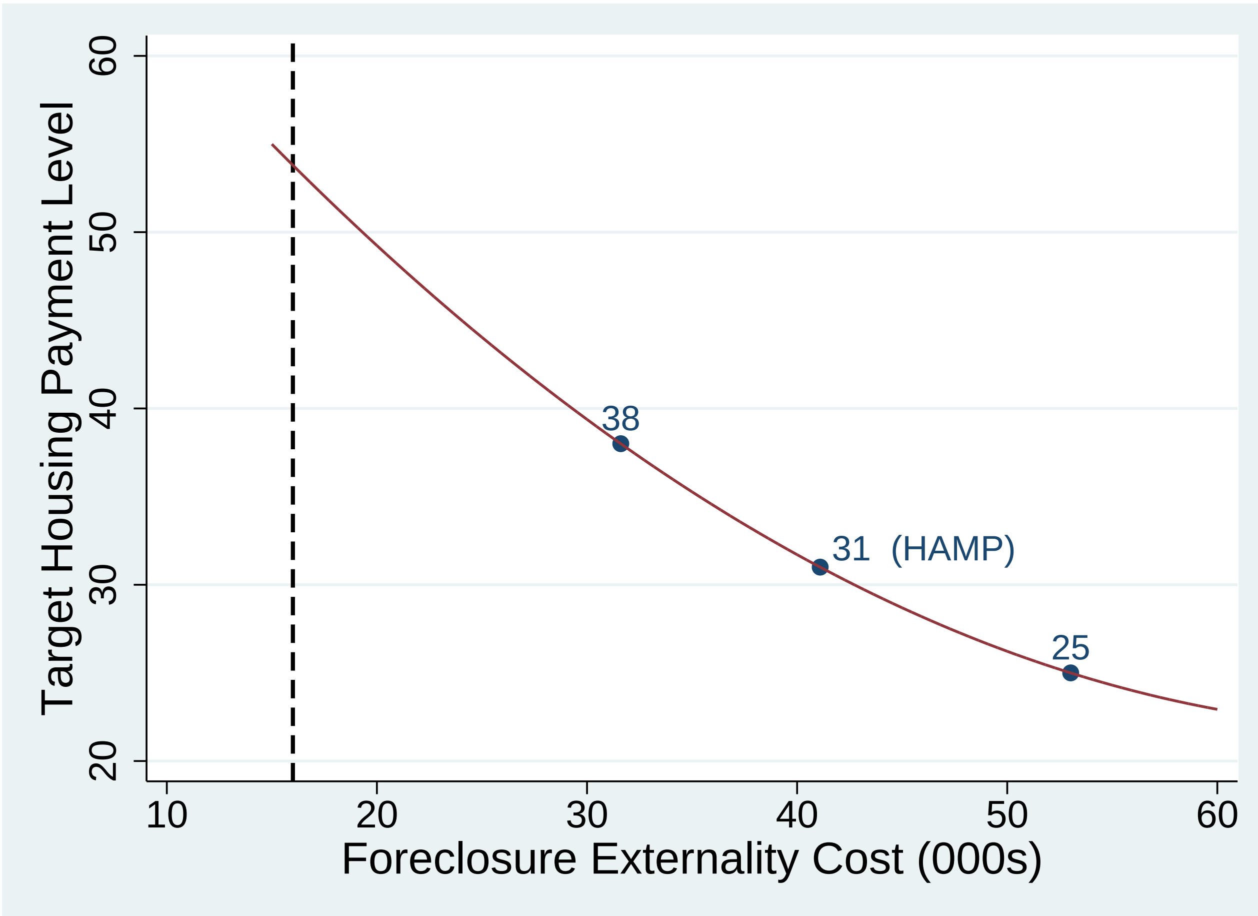
Notes: This figure displays the cumulative default rate and difference in default cumulative rate for simulated HAMP data versus the baseline counterfactual. Simulations use estimated parameter values and computed transition probabilities to determine default rate among CTS matched subsample. Baseline assigns mortgage modification as same mortgage terms prior to HAMP participation.
Source: Making Home Affordable program dataset, matched CTS subsample.

Figure 6: Cumulative Default Rates: Varying Target Payment-to-Income Ratio



Notes: This figure displays the simulated cumulative default rates as a function of months since official HAMP mortgage modification. Simulations use estimated parameter values and computed transition probabilities to determine default rate among CTS matched subsample. Lines differ by counterfactual HAMP target debt-to-income ratio used in modification process. HAMP participants with debt-to-income ratio below target value prior to modification maintain prior mortgage.
Source: Making Home Affordable program dataset, matched CTS subsample.

Figure 7: Optimal HAMP Target Housing Payment Level Policy Function



Notes: This figure displays the target HAMP debt-to-income ratio as a function of a given foreclosure externality cost. Target level determined when expected program costs equal benefits from preventing foreclosure externalities. Black dotted line represents current literature estimation of foreclosure externality at $16,000.
Source: Making Home Affordable program dataset, matched CTS subsample.

Table 1: Mortgage Terms of HAMP Participants, Before and After Modification

	(1) HAMP Mortgage Terms	(2) Prior Mortgage Terms
Annual Mortgage Payments ($)	11,482.3	20,964.9
	(6,429.2)	(15,159.8)
Interest Rate	2.867	6.575
	(1.428)	(1.563)
Amortization Term	369.3	314.3
	(85.56)	(60.58)
Outstanding Balance ($ 000s)	231.5	261.6
	(125.9)	(141.5)
Principal Forbearance (%)	6.219	0
	(12.87)	(0)
Fixed-Rate Mortgage (%)	100	58.38
	(0)	(49.29)
Observations	873,272	873,272

Notes: This table reports mortgage terms of HAMP participants at the beginning of the official HAMP modification and prior to HAMP during the application process. Mean values are reported with standard deviations in parenthesis. Prior mortgage outstanding balance includes pre-existing delinquent payments, escrow, and interest.
Source: Making Home Affordable program dataset.

Table 2: Summary Statistics of HAMP Participants, by Payment Status as of June 2013

	(1) Current	(2) Exited	(3) All
Annual Income ($ 000s)	50.62	54.13	51.76
	(24.49)	(25.86)	(25.00)
Debt-to-Income Level Prior to HAMP (%)	48.89	43.60	47.15
	(39.00)	(17.41)	(33.55)
Home Value ($ 000s)	210.4	193.1	204.8
	(124.3)	(112.3)	(120.8)
Home Equity %	-44.41	-43.75	-44.20
	(65.34)	(62.29)	(64.37)
Other Debt Payments (% of Income)	30.43	32.08	30.96
	(28.64)	(27.94)	(28.42)
CA/AZ/NV/FL (%)	56.65	47.57	53.71
	(49.56)	(49.94)	(49.86)
FICO Score	594.3	565.3	584.9
	(77.01)	(72.87)	(76.90)
GSE	0.476	0.467	0.473
	(0.499)	(0.499)	(0.499)
Observations	590,308	282,964	873,272

Notes: This table displays summary statistics of HAMP participants by June 2013 payment status. Values reported are means with standard deviations in parenthesis. Columns separated by June 2013 payment status with Current referring to households still making payments on official HAMP modified mortgage, Exited referring to households with have either defaulted out of HAMP or paid off the mortgage, and All combining those two groups. Home value is appraisal value reported by HAMP. Debt-to-Income Ratio includes primary mortgage payments, real estate taxes, homeowners insurance, and association dues and fees for housing payments. Other debt payments refer to non-primary mortgage debts and include both revolving loans and installment payments with more than 10 months remaining.
Source: Making Home Affordable program dataset.

Table 3: Comparison to CTS Data

	(1) Matched	(2) HAMP Non-GSE	(3) HAMP GSE
Annual Income ($ 000s)	63.61	60.47	50.54
	(31.46)	(29.70)	(21.02)
Exited HAMP Mortgage (%)	17.59	23.17	24.05
	(38.08)	(42.19)	(42.74)
Debt-to-Income Level Prior to HAMP (%)	47.24	47.35	45.32
	(12.09)	(12.91)	(10.27)
Interest Rate, Prior to HAMP (%)	6.744	6.290	6.284
	(1.415)	(1.872)	(1.027)
Home Value ($ 000s)	257.2	244.7	210.9
	(157.6)	(154.0)	(113.1)
Other Debt Payments (as % of Income)	86.88	85.01	88.72
	(32.89)	(34.70)	(30.68)
CA/AZ/NV/FL (%)	37.22	40.17	33.53
	(48.34)	(49.02)	(47.21)
FICO Score	592.0	585.1	589.4
	(77.13)	(77.11)	(74.02)
Has Second Lien (%)	15.31	13.62	12.42
	(36.01)	(34.30)	(32.98)
Observations	7,765	208,283	165,018

Notes: This table compares the HAMP-CTS matched sub-sample to HAMP participants with mortgages owned by GSE or Non-GSE entities. Values reported are means with standard deviations in parenthesis. Sample restricted to HAMP participants beginning after September 2010 and which include age information. GSE refers to mortgage backed by the Government-Sponsored Enterprises Fannie Mae and Freddie Mac. Exited HAMP mortgage status is as of June 2013.
Source: Making Home Affordable program dataset and Corporate Trust Services data.

Table 4: Parameter Values

		Estimate	Source
Utility			
	Variance of exit shocks η relative to u(c): α	8.828	Main Estimation
	Mean of persistent home attachment ξ: μ_ξ	0.1843	Main Estimation
	Std. dev of persitent home attachment ξ: σ_ξ	0.0714	Main Estimation
	Effective interest rate parameter: ρ_1	-0.0177	Main Estimation
	Credit risk parameter: ρ_2	2.48e-4	Main Estimation
	Coefficient of relative risk aversion: γ	2	Campbell(2011)
	Relative Weight of Housing: Θ	0.3019	CEX Estimation
	Minimum Housing Consumption: $\underline{h}$	130	CEX Estimation
	Bequest Motive: b	400	Campbell(2011)
Housing			
	Variance of house price level: σ_ε	9.925e-4	Housing Data Estimation
	Variance of price-to-rent ratio: σ_ζ	0.063	Zillow Estimation
	Maintenance costs (annual): m	0.025	Himmelberg(2005)
	Sale cost: s	0.060	–
Income			
	30 and under: μ_κ^1	0.0051	PSID Estimation
	40-50 : μ_κ^2	0.0025	PSID Estimation
	50-60: μ_κ^3	0.0006	PSID Estimation
	60 and older: μ_κ^4	-0.0051	PSID Estimation
	Variance of Household Income Shocks: σ_κ	0.00133	PSID Estimation
	Variance of Geographic Income Shocks: σ_ω	0.01574	ACS Estimation
Other			
	Discount rate (annual): β	0.94	–
	Interest rate (annual): r^f	0.03	–
	Inflation rate (annual): π	0.02	–
	Likelihood	6,003.15	
	N	5,629	

Notes: This table presents parameter values used in simulations either taken from literature values, estimated on external data, or estimated on HAMP dataset. The top section presents maximum likelihood estimates of the model's structural parameters with the HAMP estimation. Other sections present parameter values estimated on external data or taken from literature values, detailed in the Parametrization section.

Source: Author's calculations using Making Home Affordable program dataset, Panel Study of Income Dynamics, American Community Survey, Consumer Expenditure Survey, Zillow.

Table 5: Model Fit

		Observed	Simulated	Difference
Default Rate		17.77	17.52	0.251
Modification Step				
	Interest Rate	23.76	21.73	2.2026
	Term Extension	16.78	16.99	-0.201
	Early Forbearance	11.26	13.36	-2.109
	Late Forbearance	9.18	9.90	-0.317
Equity Level				
	< -100%	21.96	22.06	-0.09
	-100% - -50%	19.93	19.83	0.09
	-50% - 30%	18.16	19.05	-0.89
	-30% - -10%	14.09	17.30	-3.21
	-10% - 0%	19.32	18.01	1.31
	> 0%	15.45	8.70	6.75
Annual Income				
	< $40,000	15.17	16.16	-0.990
	$40,000-$60,000	17.67	18.27	-0.599
	$60,000-$80,000	18.85	17.74	1.107
	> $80,000	19.36	17.76	1.606
Vintage				
	2011 H1	27.53	24.15	3.381
	2011 H2	22.64	22.36	0.277
	2012 H1	15.40	15.89	-0.488
	2012 H2	6.109	7.724	-1.615

Notes: This table compares default rate observed in data to simulations using estimated parameter values and computed transition rates across observable characteristics. Modification step refers to last step reached by participant in HAMP modification procedure. Equity level and computed at time of official modification. Annual income as reported in HAMP data. Vintage is half-year in which official HAMP modification begins, with 2011H1 including October-December 2010.
Source: Author's calculations using Making Home Affordable program dataset, matched CTS subsample.

Table 6: Counterfactual Policy Simulation Default Rates and Cost Estimates

		Baseline	DTI 38%	DTI 31% (HAMP)	DTI 25%
	Participants	0	676,000	1,156,896	1,156,896
As of June 2013					
	Default Rate	66.8	30.9	22.3	18.3
	Total Defaults	773,145	357,559	257,791	211,320
	Cost Per Prevented Default ($)	0	12,754	18,345	24,104
	Program Cost($M)	0	5,300	9,453	13,542
5 Years Best Case					
	Default Rate	66.8	30.9	22.3	18.3
	Total Defaults	773,145	357,559	257,791	211,320
	Cost Per Prevented Default ($)	0	18,396	28,566	40,382
	Program Cost ($M)	0	12,716	22,595	33,818
5 Years Expectation					
	Default Rate	90.6	59.1	46.9	39.2
	Total Defaults	1,048,803	684,075	543,000	453,968
	Cost Per Prevented Default ($)	0	31,606	41,096	53,021
	Program Cost ($M)	0	11,527	20,786	31,538

Notes: This table presents defaults, costs, and payments of counterfactual policy proposals. Baseline assumes no payment reduction in modification. Cost estimated based on HAMP subsidy payment structure detailed in Appendix. Best Case assumes no more defaults occur after those observed by June 2013. Expectation assumes constant exit rate after June 2013.
Source: Making Home Affordable program dataset.

8 Appendix

8.1 HAMP Program Details

8.1.1 Eligibility

Qualifying for HAMP consists of passing an NPV test and meeting mortgage and property eligibility criteria including:

- Monthly mortgage payments greater than 31% of current income.
- Outstanding principal balance less than $729,750.[39]
- First lien mortgage not previously modified by HAMP.
- Mortgage originated before January 1st, 2009.
- Single-family, non-condemned, owner-occupied property.
- Mortgage must be delinquent or default is reasonably foreseeable.
- Documented evidence of financial hardship.

If a HAMP mortgage modification has a positive NPV test and meets the above qualifications, the servicer is required to offer the modification to the participant. While most applicants received positive NPV test results, of the thirteen percent of applicants with negative NPV test results half were still offered a HAMP modification by their servicer.

8.1.2 Modification Procedure

The heart of the HAMP program is a four-step mortgage modification procedure. Figure 8 displays the modification procedure as a flow chart. In summary, the modification procedure is a function of previous mortgage terms and income, consisting of four steps. The modification steps are followed until the monthly mortgage payments are 31 percent of the participant's monthly income:[40]

[39] This is the limit for a one unit property. Higher balances are allowed for multiple unit properties.

[40] Servicers are only allowed to deviate from the procedure if there are complicating legal issues due to securitized loan servicing agreements or if lenders wish to insert more generous terms (such as including principal forgiveness).

1. Capitalize outstanding arrears into the mortgage balance.
2. Reduce interest rate to a minimum of two percent, in $\frac{1}{8}^{\text{th}}$ increments.[41]
3. Extend amortization term to a maximum of 480 months (40 years).
4. Forbear up to 30 percent of the loan balance.

If more than 30 percent of the loan balance must be forbeared to reach the 31 percent debt-to-income level, the servicer has the option not to accept the HAMP modification. With the exception of the interest rate, these terms remain unchanged until either the mortgage is paid off or the borrower defaults out of the program. If the modified interest rate is below an interest rate cap, then five years after the modification begins, the interest rate will gradually increase to the rate cap.[42] Conditional on remaining current on the mortgage, HAMP participants also receive a $1,000 balance reduction in each of the first five years after modification.

8.1.3 Compensation Structure

HAMP servicer compensation is presented in Figures 9 and 10. Over its four year history, the compensation structure has remained largely constant but the amounts have been adjusted. In approximating program costs in simulations I include:

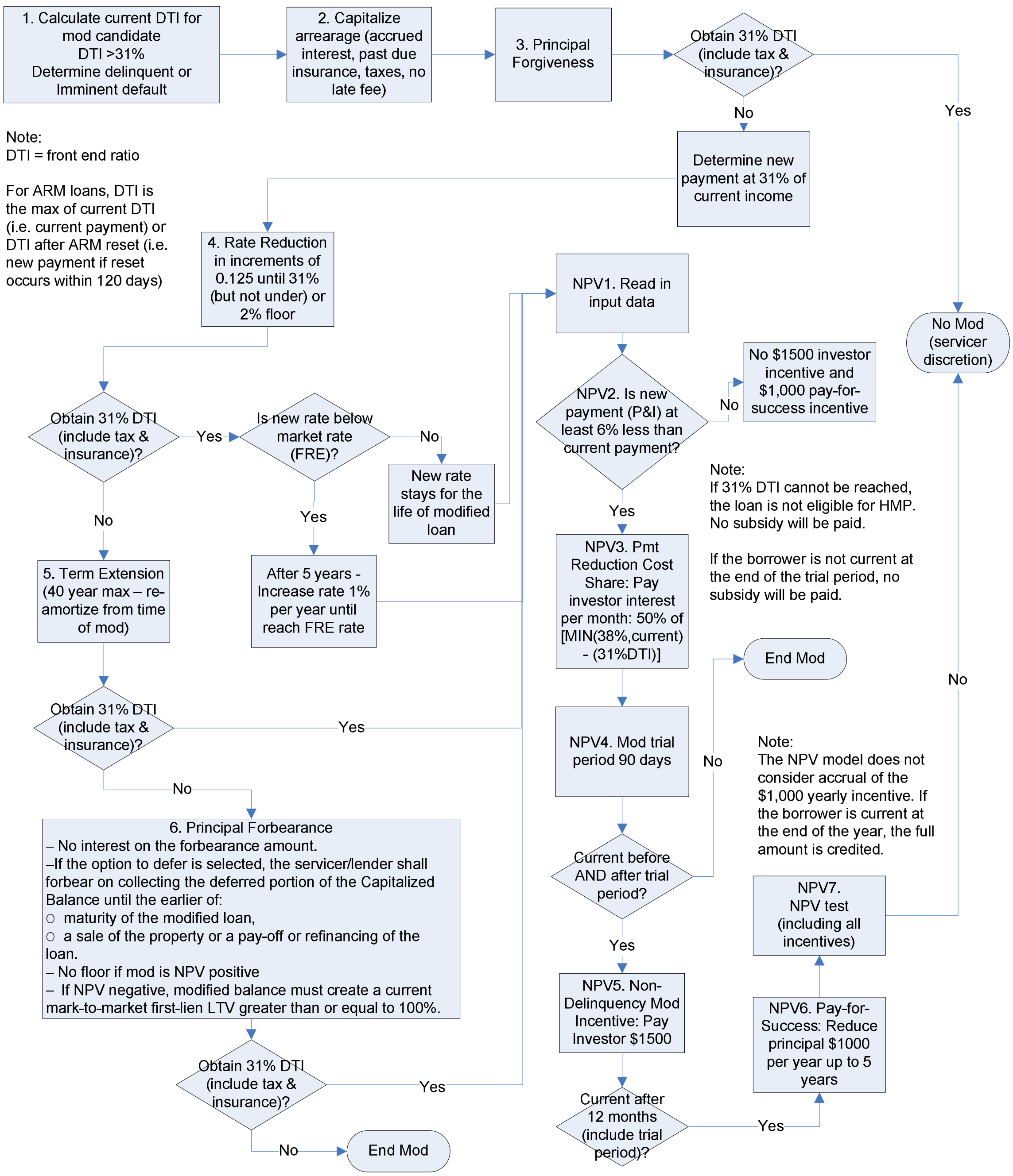
- 50 percent subsidy for each dollar of payment reduction starting at 38 percent debt-to-income ratio until 31 percent debt-to-income ratio, each month for five years maximum.
- $1,200 lump-sum payment for each modification.
- $1,000 to both borrower and servicer annually for five years maximum, conditional on good standing of borrower.

I exclude trial period payments since I am focusing only on permanent modifications. Investor House Price Decline Protection Incentive is excluded since I do not observe all necessary variables for calculation. Given the relatively stable house prices over this time period, this is likely a minimal setback.

[41] Additionally, change mortgage to fixed-rate if currently an adjustable-rate mortgage.

[42] The interest rate cap is set as the weekly reported Freddie Mac Primary Mortgage Market Survey Rate for 30-year fixed-rate conforming loans, as of the modification date.

Figure 8: HAMP Modification Flow Chart



Source: HAMP program documentation.

Figure 9: HAMP Compensation Table Part 1

Help For America's Homeowners

MAKING HOME AFFORDABLE

Home Affordable Modification Program (HAMP) Compensation

	Program	Payment Name	Frequency and Timing	Payee/Beneficiary	Amount	Accrual and Payment Notes
1	First Lien	Servicer Incentive Payment (paid for loans that successfully complete trial)	One time	Servicer/Servicer	$1,000	Paid in the first month of the official/permanent modification. Trial modification period must be successfully completed.
2	First Lien	Current Borrower One Time Bonus Payment (Servicer) (paid for loans that successfully complete trial; loan must be current at the start of the trial period)	One time	Servicer/Servicer	$500	Paid in the first month of the official/permanent modification. Trial modification period must be successfully completed.
3	First Lien	Current Borrower One Time Bonus Payment (Investor) (paid for loans that successfully complete trial; loan must be current at the start of the trial period)	One time	Servicer/Investor (Non-GSE Only)	Modification must reduce monthly housing expense by at least 6% to receive amount. $1,500	Paid in the first month of the official/ permanent modification. Trial modification period must be successfully completed.
4	First Lien	Monthly Reduction Cost Share Payment	Monthly for the first five years of the official/permanent modification.	Servicer/Investor (Non-GSE Only)	50% of the difference between the P&I Payment at 38% DTI and the P&I Payment at 31% DTI if the Front Ratio before modification is greater than or equal to 38%. or 50% of the difference between the P&I Payment before modification and the P&I Payment at 31% DTI if the Front Ratio before modification is less than 38%.	Paid monthly beginning the month after the official/permanent modification effective date if the official monthly report (OMR) is received and as long as the loan is in good standing and has not been paid off.
5	First Lien and FHA-HAMP	Borrower Pay for Performance Success Payment	Annually for the first five years of the official/permanent modification.	Servicer/Borrower	Modification must reduce monthly housing expense by at least 6% to receive amount. If such reduction is achieved, the borrower accrues, on a monthly basis, the lower of $83.33 or 50% of the difference between the Monthly Housing Expense Before Modification and Monthly Housing Expense After Modification.	Accrued for the number of months in the trial modification period in month one of the official/permanent modification to account for the time in the trial period. Accrued monthly if the OMR is received and the last paid installment (LPI) date reported on the OMR is current. Paid as principal reduction annually in the month of the anniversary of the first trial period payment due date as long as the loan

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Source: HAMP program documentation.

Figure 10: HAMP Compensation Table Part 2

	Program	Payment Name	Frequency and Timing	Payee/Beneficiary	Amount	Accrual and Payment Notes
						is in good standing and has not been paid off.
6	First Lien and FHA-HAMP	Servicer Pay for Success Payment	Annually for the first three years of the official/permanent modification.	Servicer/Servicer	Modification must reduce monthly housing expense by at least 6% to receive amount. If such reduction is achieved, the servicer accrues, on a monthly basis, the lower of $83.33 or 50% of the difference between the Monthly Housing Expense Before Modification and Monthly Housing Expense After Modification.	Accrued for the number of months in the trial modification period in month one of the official/permanent modification to account for the time in the trial period. Accrued monthly if the OMR is received. Paid annually in the month of the anniversary of the first trial period payment due date as long as the loan is in good standing and has not been paid off.
7	First Lien	Investor Home Price Decline Protection (HPDP) Incentive Payment	Annually for the first two years of the official/permanent modification.	Servicer/Investor (Non-GSE Only)	Modification must reduce monthly housing expense by at least 6% to receive amount. Formula: HPDP Index Value * UPB Quintile Payment * MTM-LTV Weighting Factor Calculation is performed as of NPV Date and based on three loan components: 1) the rate (%) of Home Price Decline derived by performing a lookup on the Home Price Decline Table (value derived from the NPV Date and the ZIP Code, updated quarterly (see the most current Base NPV Model Documentation Supplement [read-only Excel version]) 2) the quintile payment amount which will be determined by assigning the pre-modification UPB to one of five pre-determined categories (see Exhibit D of the MHA Handbook) 3) the weighting factor derived by performing a lookup of the MTM-LTV ratio (UPB before modification/Property Value) against pre-assigned weighting values (see Exhibit D of the MHA Handbook) Example: If the trial loan has 1) a projected home price decline value derived from the Home Price Index table of 10, 2) a UPB which results in a quintile assignment of 2 and a quintile base value of $300, 3) an MTM-LTV of 85% which results in a weighting factor of 2/3, the calculation would be as follows: HPDP incentive = 10 * 300 * 2/3 = $2,000	Paid annually in the month of the anniversary of the first trial period payment due date. If a loan loses good standing or is paid off before the end of the two year period, the amount accrued when the loan was in good standing shall be paid out to the investor in the month in which it lost good standing or was paid off.

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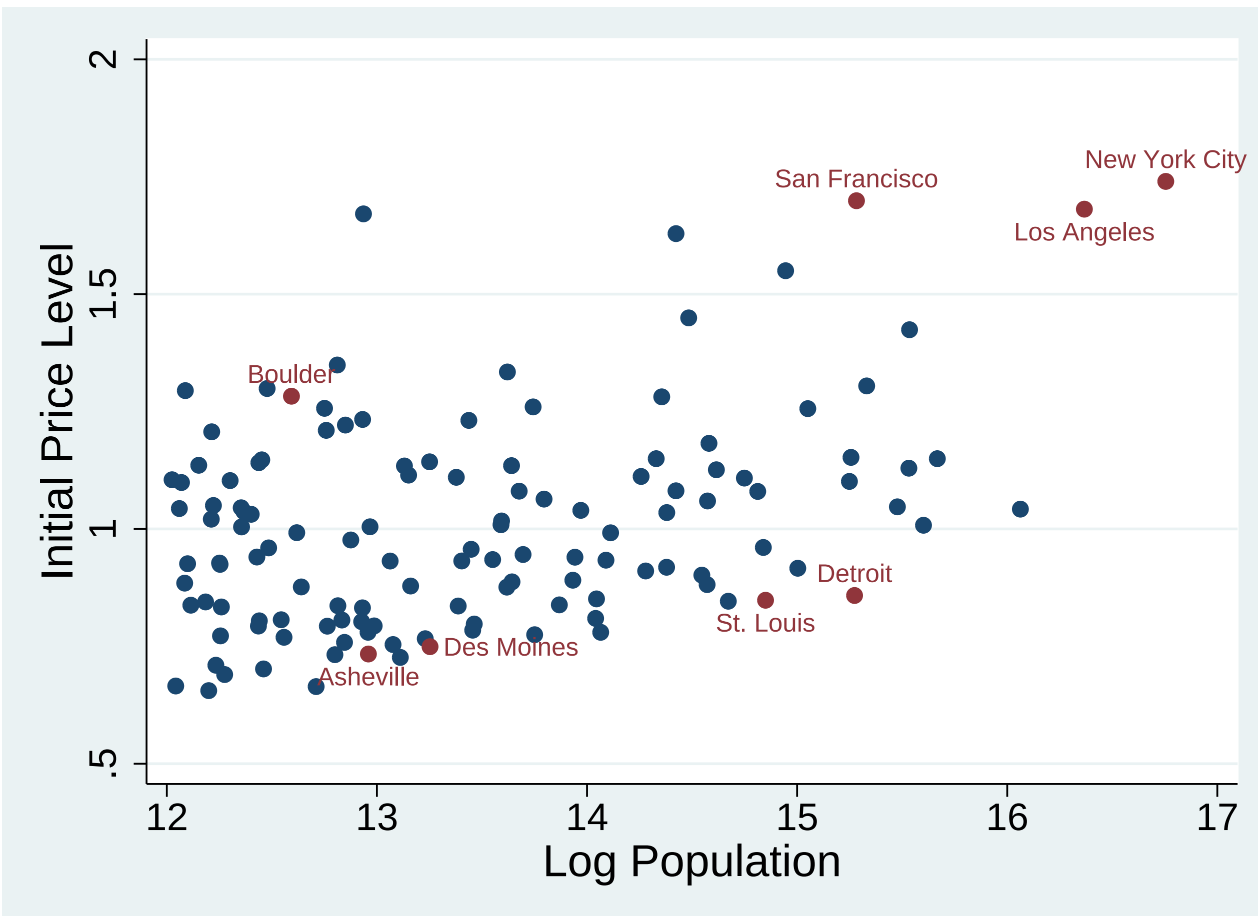
Source: HAMP program documentation.

8.2 Initial Price Level

For each location, the rental price level is calculated as a composite index based on the budget share of housing among renters by income level, in order to obtain a ranking and measure of distance between the rental price levels of locations. The index is then centered so the mean average initial house price level between locations is one. Figure 11 displays a scatterplot of the initial price levels by location compared to population with several outlying values highlighted. The lowest initial price level is for rural Michigan at 0.48 while the highest price level is New York City at 1.74.

Figure 11: Scatterplot of Initial Price Level versus Log Population, by Location



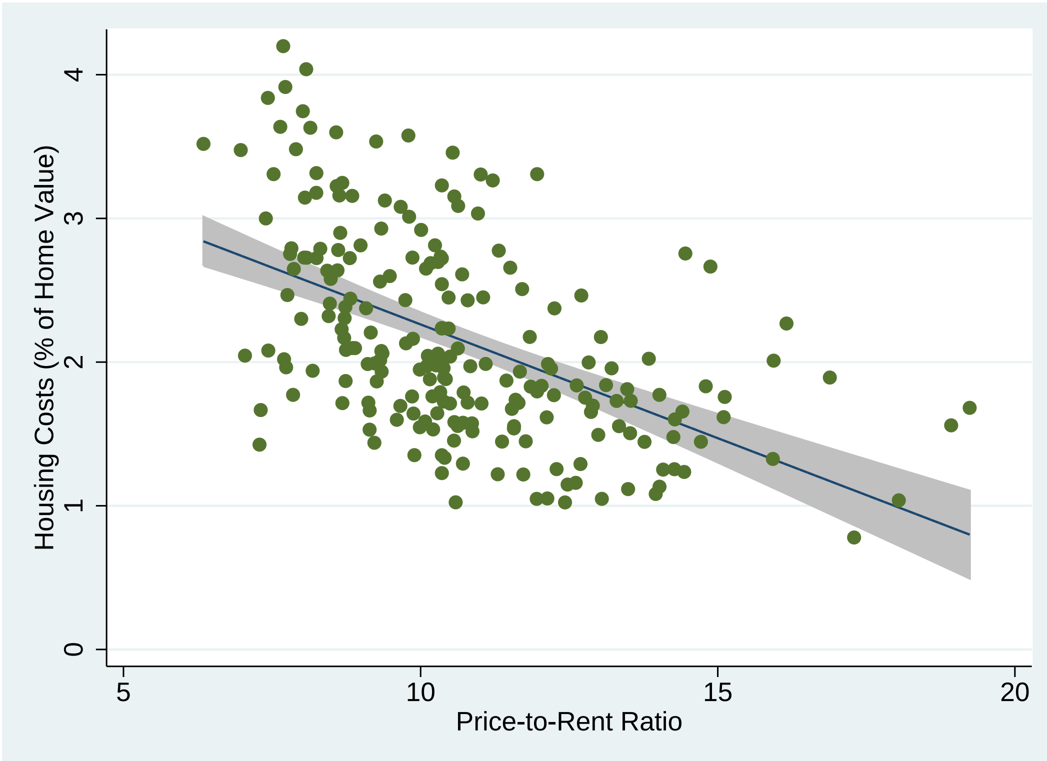
Note: Lowest population locations not included.
Source: 2010 American Community Survey.

8.3 Local Housing Costs

Local housing costs, δ_ℓ are necessary to back out expected growth rates from price-to-rent ratios in equation (4). As discussed in Himmelberg et al. (2005), these costs consist of taxes, insurance, dues, maintenance costs, and relative financial costs of holding housing as an asset relative to renting. Real estate taxes, homeowners insurance, and association dues and fees contribute to monthly housing expenses in the HAMP program, and are reported for each borrower. These values are used as household level housing payments when solving the model, however the payments are aggregated by location as a percentage of home value to be accounted for in δ_ℓ. As mentioned in Himmelberg et al. (2005), locations with higher property taxes will naturally have lower price-to-rent ratios. Figure 12 displays evidence of this effect in HAMP data. Taxes, insurance, and dues payments are assumed constant over time for each household, and can not be modified in any alternative policy proposals. Home maintenance costs, m, are assumed to be 2.5 percent annually following Harding et al. (2007). I do not explicitly account for the additional financial factors affecting house prices discussed in Himmelberg et al. (2005), such as tax treatment of mortgage interest and the risk premium for housing, but instead adjust δ_ℓ with a constant factor across locations so that the average expected house price level growth is 3.8 percent, which is the long-run appreciation rate of housing in the US.[43]

[43] Himmelberg et al. (2005)

Figure 12: Price-to-Rent Ratio versus Housing Costs, by Location

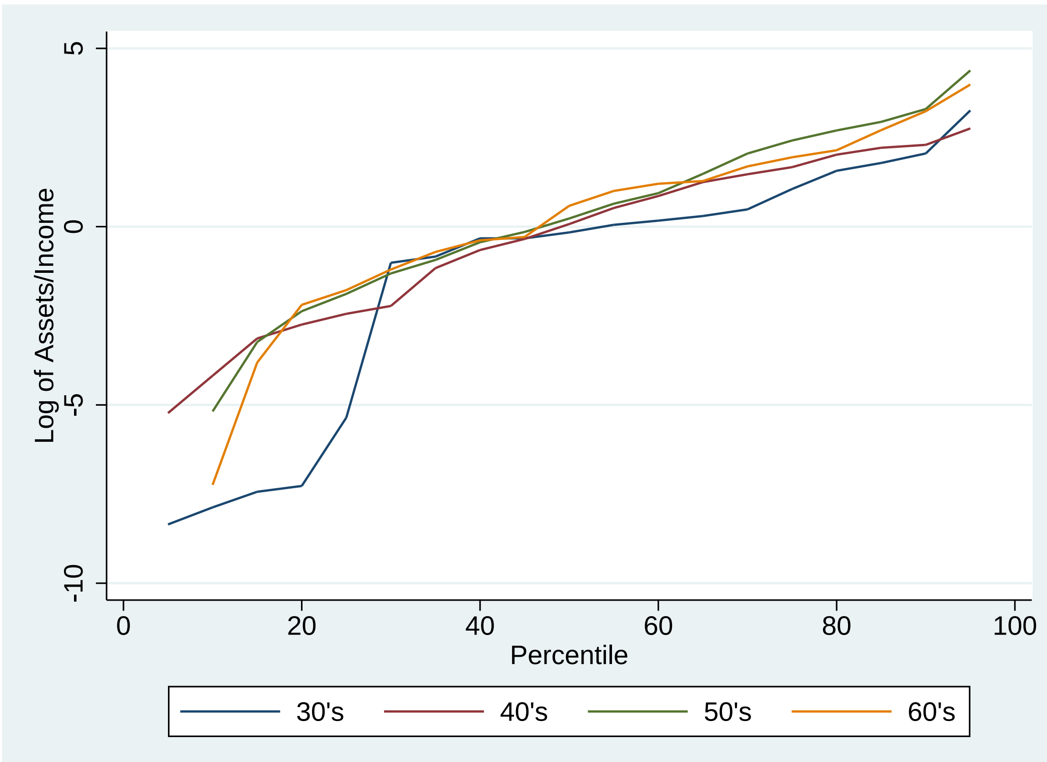


Note: Regression line fits data with linear coefficient, reported with 95% confidence interval. Price-to-rent ratio taken as average value between October 2010 and June 2013. Housing costs refers to reported annual real estate taxes, homeowners insurance, and association dues and fees. Housing costs are median value reported by MSA among HAMP participants.
Source: Price-to-Rent data from Zillow. Housing costs are from Making Home Affordable Dataset.

8.4 Initial Asset Distribution

Assets in the dynamic model aim to capture the availability of relatively liquid assets which can be used to make mortgage payments. Given this, I use the financial assets definition in the SCF which includes cash, checking accounts, stocks, and retirement account assets, and excludes assets such as vehicles, pensions, and home equity. According to Kennan (2006), the best n-point approximation of a continuous distribution uses equally spaced intervals. Thus the asset distribution for each HAMP household is approximated using the 5^{th},10^{th},...,95^{th} percentiles of observably similar household's financial assets in the SCF. Ideally the accuracy of the initial asset distribution is refined by conditioning on a host of observable characteristics. However, given the dearth of demographic variables in HAMP, and the small sample size of delinquent homeowners in the SCF, I limit the conditioning of initial asset holdings to age by decade.[44]

Figure 13: Probability Distribution of Assets Relative to Income, by Age Decade

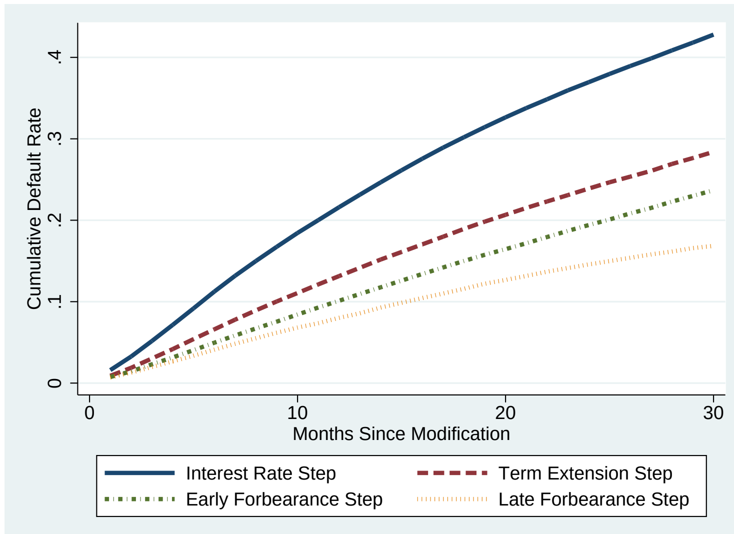


Note: Sample restricted to homeowners reporting being at least 60 days delinquent on a debt payment within the past year.
Source: 2010 Survey of Consumer Finances.

[44]Note that HAMP places no restriction on assets to participate, so there is no reason to censor the upper tail of the asset distribution.

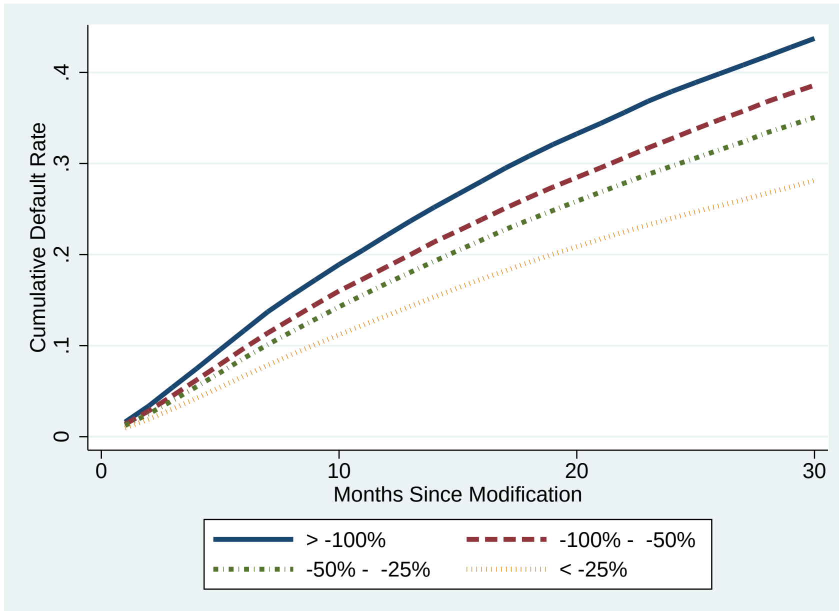
8.5 HAMP Participant Variation in Default Rates

Figure 14: Observed Cumulative Default Rate, by HAMP Modification Level



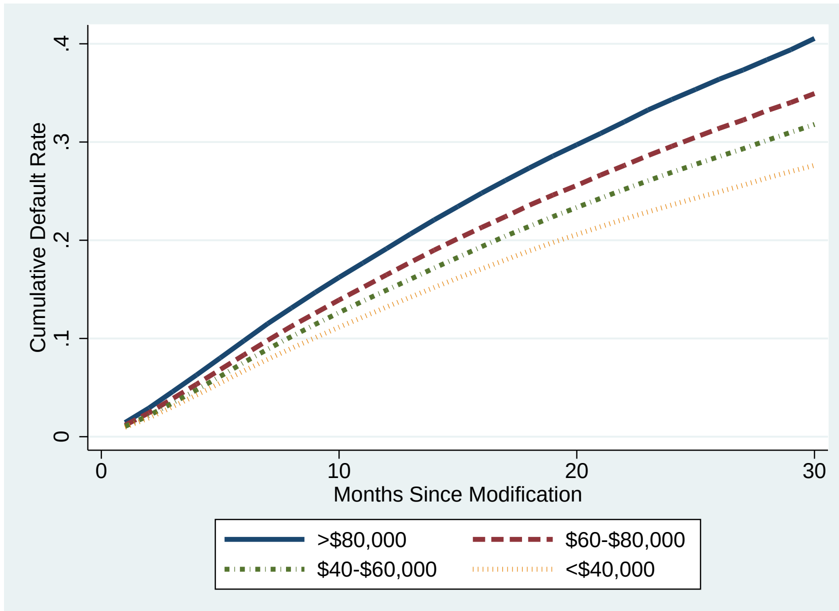
Notes: This figure displays the cumulative default rate of HAMP participants as a function of months since official modification began. Participants are grouped by the furthest of four steps in the HAMP modification process they reached. The first step is interest rate reduction, then amortization term extension, then principal forbearance. Modifications requiring more than thirty percent of balance forbeared to enter HAMP are classifying as Late Forbearance step since for these mortgages, lenders can exercise discretion towards HAMP acceptance.
Source: Making Home Affordable program dataset. MSA population from 2010 Census data.

Figure 15: Observed Cumulative Default Rate, by Equity Category



Notes: This figure displays the cumulative default rate of HAMP participants as a function of months since official modification began. Participants are grouped by home equity level at time of modification.
Source: Making Home Affordable program dataset.

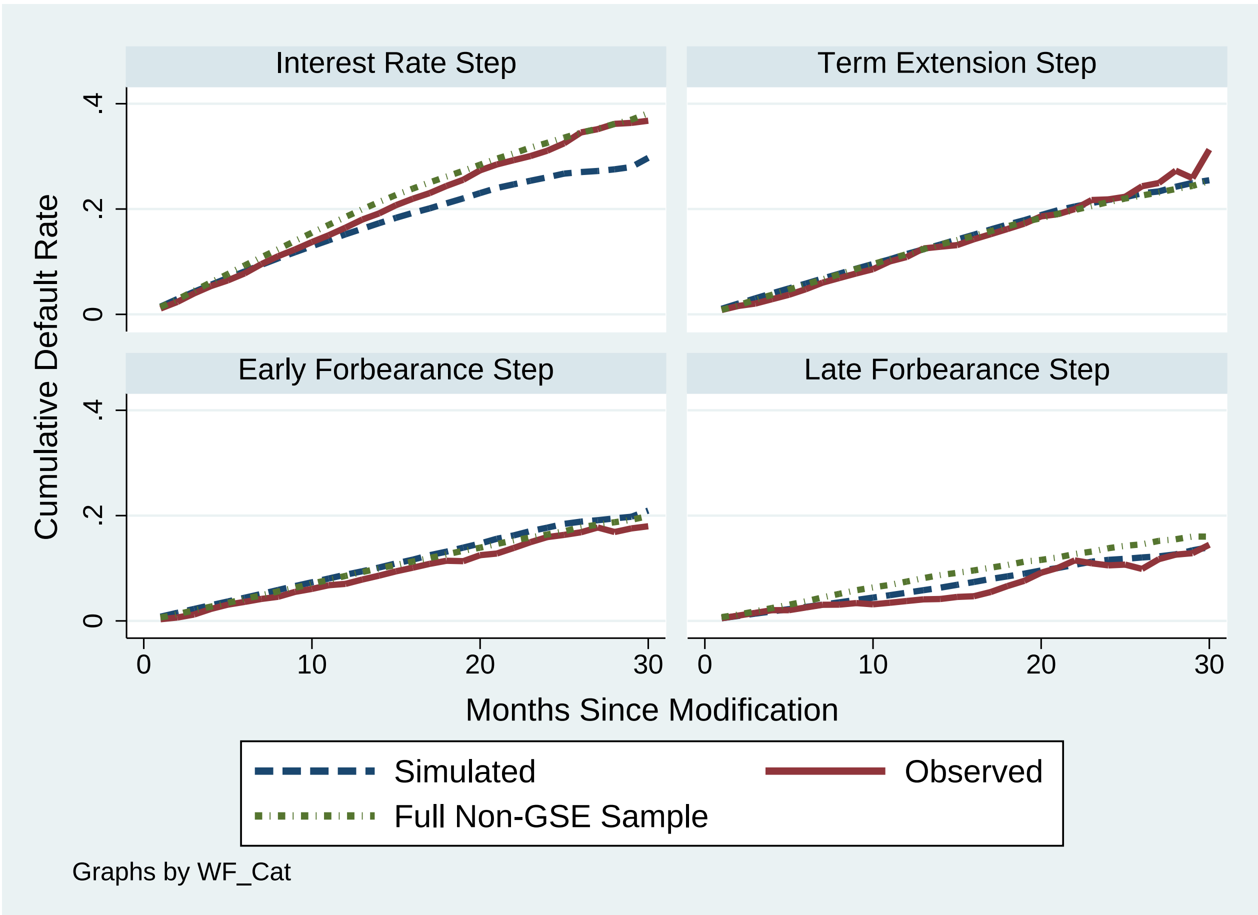
Figure 16: Observed Cumulative Default Rate, by Income Category



Notes: This figure displays the cumulative default rate of HAMP participants as a function of months since official modification began. Participants are grouped by income used in HAMP modification calculation.
Source: Making Home Affordable program dataset.

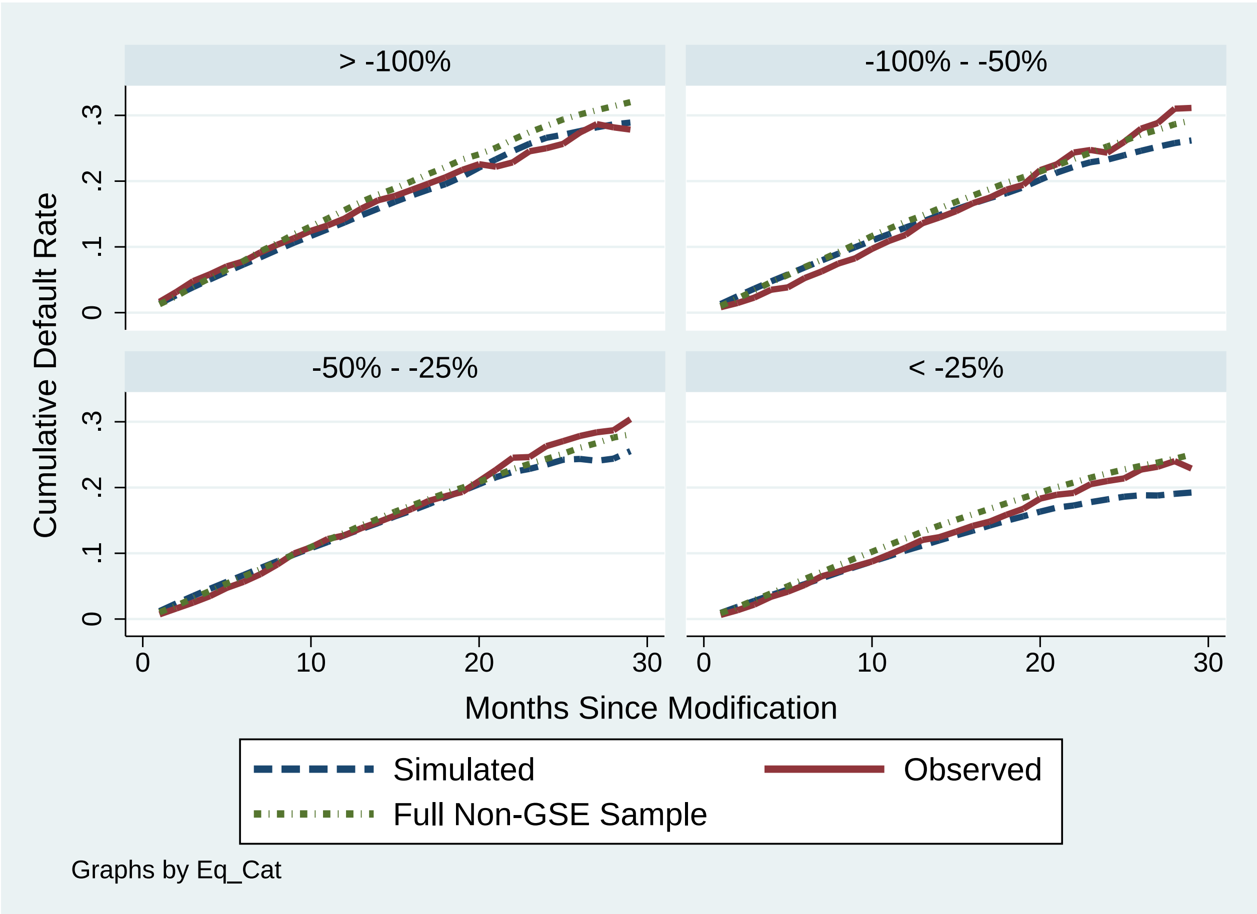
8.6 Simulation Comparisons

Figure 17: Simulated vs. Observed Default Rates, by HAMP Modification Level



Notes: This figure displays the cumulative default rate of HAMP participants as a function of months since official modification began. The Full Non-GSE Sample uses all HAMP participants with mortgages not owned by a GSE enterprise, from which the CTS subsample is matched upon. Simulations use estimated parameter values and computed transition probabilities to determine monthly default rate. Panels are grouped by the HAMP modification process step participants reached. The first step is interest rate reduction, then amortization term extension, then principal forbearance. Modifications requiring more than thirty percent of balance forbeared to enter HAMP are classifying as Late Forbearance step since for these mortgages, lenders can exercise discretion towards HAMP acceptance.
Source: Making Home Affordable program dataset, matched CTS subsample.

Figure 18: Simulated vs. Observed Cumulative Default Rate, by Equity Category

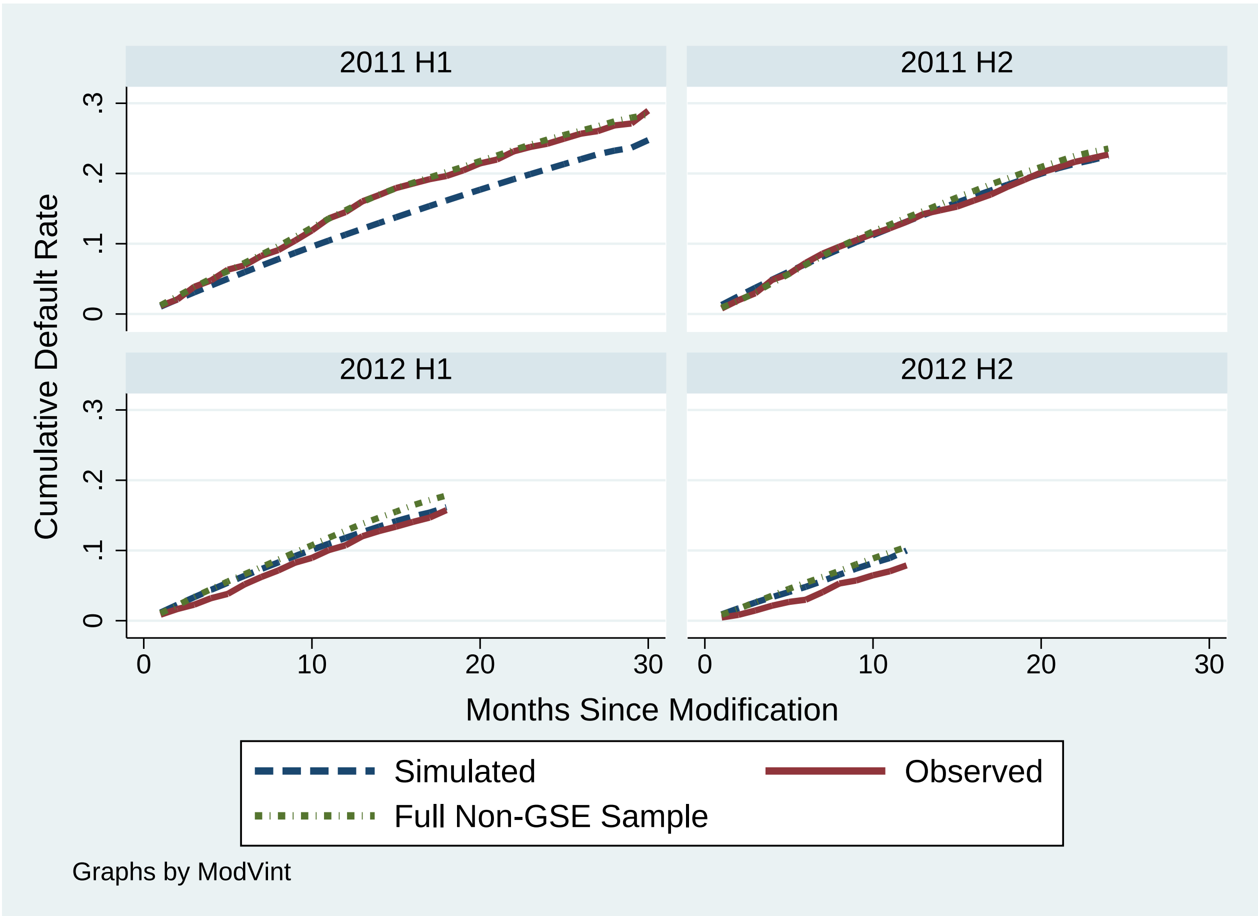


Notes: This figure displays the cumulative default rate of HAMP participants as a function of months since official modification began. The Full Non-GSE Sample uses all HAMP participants with mortgages not owned by a GSE enterprise, from which the CTS subsample is matched upon. Simulations use estimated parameter values and computed transition probabilities to determine monthly default rate. Panels are grouped by home equity level of participant at time of modification.
Source: Making Home Affordable program dataset, matched CTS subsample.

Figure 19: Simulated vs. Observed Cumulative Default Rate, by Income Category

Notes: This figure displays the cumulative default rate of HAMP participants as a function of months since official modification began. The Full Non-GSE Sample uses all HAMP participants with mortgages not owned by a GSE enterprise, from which the CTS subsample is matched upon. Simulations use estimated parameter values and computed transition probabilities to determine monthly default rate. Panels are grouped by participant income used in HAMP modification calculation.
Source: Making Home Affordable program dataset, matched CTS subsample.

Figure 20: Simulated vs. Observed Cumulative Default Rate, by Modification Vintage



Notes: This figure displays the cumulative default rate of HAMP participants as a function of months since official modification began. The Full Non-GSE Sample uses all HAMP participants with mortgages not owned by a GSE enterprise, from which the CTS subsample is matched upon. Simulations use estimated parameter values and computed transition probabilities to determine monthly default rate. Panels are groups by official HAMP modification vintage half-year. 2011 H1 includes October-December 2010.
Source: Making Home Affordable program dataset, matched CTS subsample.