Low-Income Homeownership and the Role of State Subsidies: A Comparative Analysis of Mortgage Outcomes

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Abstract

Between the late 1970s through 2013, state Housing Finance Agencies (HFAs) financed nearly $300 billion in mortgages to low- and moderate-income first-time homebuyers. Descriptive evidence indicates that HFAs help households retain their homes at higher rates than similar households purchasing homes in the private mortgage market. Using a matched sample of HFA originations between 2005 and 2014, we estimate a multinomial logit model of mortgage default (or foreclosure) and prepayment. We find that HFA borrowers are about 30 percent less likely to default or foreclose on their mortgages than otherwise similar non-HFA borrowers. We find that 37 percent of this HFA effect can be explained by HFA origination and service delivery practices including direct servicing and homeownership counseling. © *2020 by the Association for Public Policy Analysis and Management*

INTRODUCTION

Enabling access to affordable and sustainable homeownership has long been a goal of U.S. housing policy. Lower income households can face significant barriers to purchasing homes, including lack of wealth for a down payment, limited incomes to afford monthly mortgage payments, and weak or thin credit histories that make it difficult to qualify for conventional mortgage financing (Acolin et al., 2016; Fuster & Zafar, 2016; Rohe, 2017). Homeownership rates, particularly among lower income households, soared during the housing boom but unprecedented mortgage delinquency and foreclosure rates during the housing bust quickly erased those homeownership gains. The spike in delinquency and foreclosure activity exposed deficiencies in many lender servicing practices in foreclosure or loan mediation processes which exacerbated the housing crisis. This mortgage servicing fiasco resulted in the 2012 National Mortgage Settlement, the second largest civil settlement in U.S. history at $26 billion.

Affordable lending programs administered through state Housing Finance Agencies (HFAs) provide a potential vehicle to extend mortgage credit to lower income households sustainably. Since the late 1970s, state HFAs have provided affordable mortgages to more than 3.2 million low- and moderate-income (LMI) households, the majority of whom were first-time homebuyers (NCSHA, 2015).[1] Descriptive

[1] HFA loan volume is through 2014, according to the National Council of State Housing Agencies (NCSHA, 2015). LMI is defined as a household with income below 115 percent of the area median.

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evidence suggests that HFA mortgages perform better than expected. HFAs were granted an exemption from the Qualified Residential Mortgage requirements in part because of the assertion that HFA-originated mortgages had less risk along with strong underwriting, and a proven track record of safe and sound performance (NCSHA, 2015).[2]

To extend homeownership to LMI households, HFA mortgages often include a slight interest rate subsidy or down payment assistance. In addition to these modest financial benefits, HFA borrowers often receive greater personal attention and assistance including homeownership counseling and preventative servicing practices such as early loan default counseling and loan modification assistance. Many HFAs also directly service their mortgages, an uncommon practice in the private subprime mortgage market, which may help align the incentives of mortgage originators and servicers in handling and communicating with borrowers.

Despite their alleged superior performance, there have been no rigorous studies comparing the loan performance of HFA-originated mortgages to the loans of otherwise similar borrowers. This paper seeks to address this gap in the literature. Do HFA mortgages perform better than similar private market mortgages? Further, and of particular policy relevance, what aspects of HFA origination and service delivery practices are associated with better loan performance?

To analyze loan performance, we construct a matched dataset of HFA and non-HFA originations using a sample of 140,000 first-time homebuyer mortgages securitized by Fannie Mae between 2005 and 2014. HFAs serve lower-income and underserved borrowers who usually have worse loan performance than the average non-HFA borrower. Accounting for these and other observable risk differences is critical to analyzing HFA performance. We use a combination of propensity score and exact matching to ensure that the two groups of borrowers have similar characteristics at origination. To explore implementation differences between HFAs, we include panel data on HFA origination and service delivery practices that vary within and between HFAs over time.

We find that HFA loans have a substantially lower risk of default and foreclosure than loans originated to otherwise similar LMI borrowers. In our base multinomial logistic model specification, the relative risk of default (vs. prepayment) is 29 percent lower for HFA borrowers than it is for otherwise similar non-HFA borrowers and the relative risk of foreclosure (vs. prepayment) is 32 percent lower for HFA borrowers. For comparison, using results from the Fuster and Willen (2017) analysis of mortgage payments and default, we estimate the HFA effect on default is similar to a 2.5 percentage point reduction in the interest rate—far greater than the average 0.47 percentage point interest rate subsidy we estimate the average HFA loan receives during our sample period. Further, the HFA effect on default remains persistent across time periods, even for originations after 2012 when interest rates for HFA mortgages became comparable to that of non-HFA loans.

Foreclosures are an important public policy issue for many local governments. Foreclosures are costly and disruptive as they incur substantial court time and fees, may require demolition, and drag down local housing markets. Previous work by Apgar et al. (2005) suggests that the municipal cost of an average foreclosure is between $5,358 to $7,020 dollars. Extrapolating our results to the 800,000 HFA loans originated between 2005 and 2014 suggests there would have been 53 thousand more defaults and 33 thousand more foreclosures had those loans been originated through private lenders. Using the Apgar et al. (2005) results, this translates to up to $232 million in saved local costs, a significant benefit to communities hit hard

[2] See https://www.ncsha.org/blog/ncsha-supports-bond-exemption-risk-retention-rule.

by the housing crisis. Further, prior research (Anenberg & Kung, 2014; Campbell, Giglio, & Pathak, 2011; Harding, Rosenblatt, & Yao, 2009; Immergluck & Smith, 2006; Rosenblatt et al., 2012) has found that foreclosures impose negative externalities on nearby property values and can lead to increased crime in their neighborhoods (Ellen, Lacoe, & Sharygin, 2013). These negative foreclosure externalities are likely not considered by private market lenders, but public lenders, such as HFAs, may take these externalities into consideration when crafting their programs. As a result, HFAs may increase societal welfare by reducing foreclosures particularly since they target LMI borrowers who are typically at greater risk of foreclosure.

Understanding why HFA loans perform better than observably similar non-HFA loans provides critical information for policymakers. If there are HFA practices that contribute to the reduced risk of default, they could be implemented by other HFAs and even non-HFA lenders to reduce lending costs and expand mortgage access. We examine two pathways through which HFAs may reduce risk: (1) structural attributes of the mortgage, and (2) service delivery practices implemented by HFAs. Structural attributes are those that reduce the probability of default directly through rigorous underwriting, as well as through the loan structure and supplementary financing, such as down payment assistance. We find that the structural characteristics of mortgages are important, but their inclusion in our models explain only about 10 percent of the HFA effect on default and foreclosure.

Our results indicate that variation in service delivery between HFAs offers more explanatory power than structural characteristics, together explaining 37 percent of the HFA effect. Specifically, we exploit within-state variation in whether or not HFAs directly provide specific aspects of program delivery in-house, including loan servicing, funding for homeownership counseling, and offering a refinance loan program. If not offered directly by the HFA, loan servicing is contracted out, homeownership counseling is available from nonprofit housing organizations (sometimes for a fee), and refinance loans are available to homebuyers in the open market. We find that mortgages from state HFAs that service their own mortgages in-house are significantly less likely to experience default or foreclosure than are homeowners with mortgages from the same HFA, but in a year that the HFA did not service their mortgages in-house—and that this effect size is nearly as large as the total HFA effect. Similarly, borrowers with loans from HFAs that directly fund homeownership counseling are less likely to experience subsequent default and foreclosure. Borrowers from state HFAs that offer their own refinance loan programs are more likely to prepay their mortgages, which is notable given that interest rates were declining, and HFA borrowers were significantly less likely to refinance even when it was in their financial interest to do so.

These findings on the benefits of direct service delivery contribute to a broader literature on the mixed delivery of public services and potential trade-offs between privatization and direct provision, particularly for vulnerable populations (Amirkhanyan, Kim, & Lambright, 2008; Amirkhanyan et al. 2018; Bel & Rosell, 2016; Marvel & Marvel, 2007). Affordable mortgage lending is a context that is ripe for privately provided services, given the robust private market for mortgages in the U.S. Further, private mortgage lending is increasingly becoming less personalized and more transactional, with an unprecedented growth in non-bank and online "fintech" lending over the last decade (Fuster et al., 2019; Jagtiani, Lambie-Hanson, & Lambie-Hanson, 2019). Yet for LMI first-time homeowners, our results suggest that higher touch servicing practices can help offset the higher default risk of lending to this population. Much of the current emphasis in lending innovation is on streamlining and improving the origination process (Buchak et al., 2018; Fuster et al., 2019); however, preventative servicing on the back-end may be an equally if not more important policy tool to extend access to mortgage credit to underserved borrowers without increasing risk. Strategies used by HFAs with in-house servicing can help inform policy innovations in servicing practices more generally (Goodman et al., 2018; Moulton et al., 2015; Reid, Urban, & Collins, 2017).

BACKGROUND AND EXPECTATIONS

State HFAs and LMI Mortgage Lending

As of 2002, all U.S. states have an HFA, and most administer a mortgage program for first-time homebuyers.[3] State HFAs began financing mortgages in the early 1970s through the sale of tax-exempt mortgage revenue bonds (MRBs), which HFAs then pass along in the form of reduced interest rate mortgages to LMI first-time homebuyers, retaining a portion of the spread to help finance agency operations.[4] HFA mortgage programs are largely financed from revenue generated through mortgage originations, including those originated as tax-exempt MRBs. As a result, they have a strong incentive to monitor loan performance (Moulton & Quercia, 2014). By statute, HFA mortgages financed with MRBs must serve first-time homebuyers with incomes below 115 percent of area median income, with exceptions for households living in targeted geographic areas. Historically, the spread between HFA and market interest rates has been as high as two to three percentage points, providing a substantial reduction in the size of the monthly mortgage payments to low-income homeowners (Durning, 1987; Moulton & Quercia, 2014).

The drop in interest rates following the Great Recession led HFAs to utilize other non-MRB mortgage-backed securities to finance mortgages, resulting in interest rates on HFA loans that are comparable to prime conventional mortgage rates (Moulton & Quercia, 2014).[5] Aside from lower interest rates, some HFA programs also facilitate affordable homeownership with down payment assistance (DPA) to borrowers through grants, forgivable loans, or secondary financing. The proportion of HFA mortgages with DPA has fluctuated over time; in 2006, approximately 50 percent of HFA loans were reported to have some form of DPA compared to 70 percent in 2012 (Moulton & Quercia, 2014). In addition to financial subsidies, HFAs frequently provide counseling and support to homeowners pre- and post-purchase. A 2010 survey found that one-third of HFAs required homeownership counseling for all borrowers, with more than 80 percent requiring at least a portion of their borrowers to participate in these services (Dylla & Caldwell-Tauges, 2012).

Prior research on HFA mortgages is limited. Early studies of MRB financed mortgages questioned the value of the taxpayer-funded subsidy, with concerns that the reduced payment was not necessary to stimulate home purchases, or that HFA builder-partners capitalized the subsidy into higher house prices (Benjamin & Sirmans, 1987; Durning, 1987; Durning & Quigley, 1985). While increasing the extensive margin of home purchases is a potential public benefit from HFA mortgage programs, a perhaps equally important public benefit is reduced default rates of HFA-financed loans—a topic that has not been studied in prior research, due in large part to lack of data. Each HFA administers its own program, complicating

[3] Not all state HFAs administer a first-time homebuyer program every year. During our study period, Arizona and Illinois did not report any mortgage originations in 2013 (NCSHA, 2015).
[4] The spread amount (arbitrage) permitted by statute has changed over time and is currently limited to 1.25 percent (Moulton & Quercia, 2014).
[5] As of a 2012 survey of state HFAs, nearly 40 percent reported selling non-MRB mortgage-backed securities directly into the market—a strategy that none of the HFAs reported using in 2006 (Moulton & Quercia, 2014). In contrast to MRB-financed mortgages that provide revenue to HFAs through the interest rate spread during the life of the loan, non-MRB mortgage-backed securities provide an up-front financial return when pools of mortgages are sold directly into the mortgage-backed securities market.

comparative analysis of HFA loan performance across programs, or relative to non-HFA mortgages. A few recent studies have explored within-program variation in HFA loans on mortgage default, including studies of pre- and post-purchase homeownership counseling (Brown, 2016; Moulton et al., 2015), and studies of variations in originating lender characteristics (Ergungor & Moulton, 2014; Moulton, 2010). However, no prior study examines the performance of HFA mortgages relative to non-HFA mortgages. This is a primary contribution of our study.

Theoretical Expectations for Default and Prepayment of HFA Mortgages

Mortgage outcomes include the competing risks of default and prepayment. Following an options-theoretic framework, homeowners make decisions each period to default on their mortgages (put option), to prepay their mortgages either from refinancing, home sale, or paying off the mortgage (call option), or to continue making payments. Critical inputs to these decisions include the current home value, the mortgage balance, the mortgage interest rate, and the expected interest rate from refinancing. Transaction costs also influence decisions, including costs from damage to future credit from defaulting, and the origination and search costs of refinancing a mortgage or selling the home (Deng, Quigley, & Van Order, 2000; Quercia & Spader, 2008). The decision to default is optimal when the costs from continuing to make mortgage payments exceed the expected current home value plus expected transaction costs from defaulting. The decision to prepay is optimal when the cost from continuing to make the mortgage payments exceeds the expected cost of the mortgage at the expected market interest rate plus transaction costs from refinancing or selling the home.

Studies of mortgage outcomes acknowledge frictions that lead homeowners to make decisions that appear suboptimal (Campbell & Cocco, 2015; Elul, 2016; Fuster & Willen, 2017). For example, borrowing constraints such as poor credit or lack of income may prevent homeowners from refinancing even when it would be cost advantageous to do so (Archer, Ling, & McGill, 1996). A loss of income, reduced liquidity, or an increase in non-housing expenses may cause homeowners to re-weigh the effective cost of continuing to make mortgage payments given reduced cash flow, relative to the expected future value of the home (Campbell & Cocco, 2015; Elul et al., 2010). Homeowners with a shock to net income who have sufficient equity to prepay their mortgage through home sale may choose to do so even if it is not "in the money"; similarly, those with an income shock and negative equity are more likely to default—sometimes referred to as a double trigger (Campbell & Cocco, 2015; Fuster & Willen, 2017). Finally, homeowners may simply lack financial sophistication or adequate information to appropriately evaluate their call and put options (Agarwal, Ben-David, & Yao, 2017; Deng, Quigley, & Van Order, 2000).

Recent research documents that a substantial proportion of households fail to refinance when interest rates drop. Some of these households are credit constrained and thus remain "trapped" in higher-cost mortgages (Lambie-Hanson & Reid, 2018). However, even those who are otherwise eligible often fail to refinance when it is optimal to do so (Agarwal, Rosen, & Yao, 2016). These mistakes can be costly; a recent study estimates that 20 percent of credit-worthy homeowners who failed to refinance in 2010 would have substantially reduced their mortgage payments by a median amount of $160 per month (Keys, Pope, & Pope, 2016).

Building from this framework, we expect HFAs to affect mortgage performance through several pathways, including lowering mortgage costs through reduced interest rates, lessening the transaction costs associated with curing a default, and reducing frictions such as borrowing constraints and lack of information. First, lower interest rates on HFA mortgages reduce the size of the monthly mortgage payment compared to non-HFA borrowers with higher interest rates and the same mortgage amount, increasing the value of the option to continue to make payments. Aside from lower average rates, HFA mortgage interest rates are not determined by risk-based pricing but instead are the same for all borrowers in a particular program at a given point in time. This means that the spread between the HFA and the market interest rate is larger for higher risk borrowers with lower incomes or credit scores than for lower risk borrowers, reducing relative default probabilities even more for this group. Further, a subsidized interest rate on HFA loans may also reduce refinancing probabilities in subsequent periods, given the smaller expected spread between refinancing at the current market rate and the subsidized origination interest rate.

Prior research indicates a relationship between lower interest rates and reduced mortgage default. In a study of adjustable rate mortgages with interest rate resets after five years, Fuster and Willen (2017) find that a three percentage point reduction in interest rate—equivalent to cutting the mortgage payment in half during their study period—results in a 55 percent reduction in the hazard of 90-day default. In their analysis, this effect size is equivalent to a reduction in the current loan-to-value (LTV) ratio from 135 percent to 90 percent. Using data from the Panel Survey of Income Dynamics, Gerardi et al. (2017) find that a 10 percent reduction in residual income in conjunction with an employment shock increases the likelihood of mortgage default by 1.2 to 2.5 percentage points. These findings comport with literature on mortgage modifications that overwhelmingly finds payment reductions to be more effective than principal reductions in reducing the re-default rates of delinquent borrowers (Adelino, Gerardi, & Willen, 2013; Agarwal et al., 2011; Haughwout, Okah, & Tracy, 2016).

Second, HFAs may reduce the transaction costs associated with remaining current or curing a delinquent mortgage. As public and quasi-public entities, HFAs are politically accountable for the performance of loans. This creates an added incentive for careful screening and servicing of HFA loans (Ergungor & Moulton, 2014).[6] Prior research indicates that agency incentives for screening are associated with reduced mortgage default. For example, loans held in lenders' portfolios have lower default rates than otherwise similar loans securitized through the secondary market (Elul, 2016; Keys et al., 2010). Political accountability for loan performance creates incentives for HFAs to carefully screen borrowers—even for HFA loans that are securitized.

The majority of HFAs have centralized servicing where HFAs service loans in-house or they contract with a single Master-Servicer who purchases the mortgage servicing rights (Moulton & Quercia, 2014). Centralized servicing allows for increased agency monitoring of loan performance and servicing practices. Nearly half of HFAs in 2012 identified additional preventative servicing practices that were provided to HFA borrowers beyond what would typically be provided to borrowers in the private market, including early default counseling and assistance with loan modification or short-sale in the case of pending foreclosure (Moulton & Quercia, 2014). Prior research on mortgage modifications finds that one of the primary challenges is getting borrowers at risk of foreclosure to contact their lender (Cutts & Merrill, 2009). HFA servicing practices may increase lender-borrower interactions and reduce the transaction costs of curing a mortgage delinquency.

[6] The origination of mortgages through MRBs or non-MRB mortgage-backed securities generates an independent revenue stream to the HFA that can help fund agency operations. Negative publicity about the program (e.g., through high rates of default) may be viewed as a threat to the independence of the revenue stream and accumulated capital reserves.

Third, HFAs may improve borrower outcomes through the provision of information. HFAs often embed some form of homeownership counseling into their origination process (Brown, 2016; Dylla & Caldwell-Tauges, 2012). Standard homeownership counseling and education typically includes information on budgeting, consumer credit, avoiding foreclosure, and when it is cost-effective to refinance a mortgage or sell the home. This information may improve the expected optimality of the exercise of put and call options. In an analysis of an affordable mortgage program, Quercia and Spader (2008) find that borrowers participating in homebuyer education and counseling were more likely to prepay their mortgages when it was cost advantageous to do so. In an analysis of a single state HFA program, Brown (2016) finds that the introduction of a required pre-purchase homeownership counseling program is associated with reduced risk of foreclosure and an increased probability of curing a default.

While information may increase borrower awareness of their option to refinance, policy restrictions on HFA-financed mortgages may reduce the likelihood of prepayment. The federal tax code that enables HFAs to sell mortgage revenue bonds prohibits using the funds to refinance mortgages (U.S.C., Section 143a, 1986). LMI consumers with HFA loans could refinance into a non-HFA mortgage product as interest rates drop. However, HFA borrowers are less likely to be eligible for "streamlined" refinancing programs as they would need to switch lenders. HFA borrowers thus face higher information costs to learn about refinancing opportunities, and higher actual origination costs to act on those opportunities. This may result in HFA borrowers failing to refinance even when it would be "in the money" to do so.[7] However, beginning in 2012, several state HFAs began offering refinancing programs without the use of mortgage revenue bonds, thereby circumventing the policy restriction. HFA borrowers with loans from state HFAs that offered refinancing options may be more likely to refinance, as information and transaction costs should be lower for these borrowers.

DATA AND METHODS

Data

To determine the effect of HFAs on mortgage outcomes, we utilize proprietary Fannie Mae loan origination and performance data. Our sample includes the universe of 30-year, fixed-rate, single-family, owner-occupied purchase loans originated between 2005 and 2014 acquired by Fannie Mae.[8] To more accurately reflect HFA borrower characteristics, we limit this population to loans originated to first-time homebuyers with household incomes less than $200,000 per year, with full documentation, and without any missing variables.[9] These sample restrictions result in a population of 689,850 loans, of which 113,984 are originated through HFAs.

[7] Refinancing also becomes more complicated if the borrower has down payment assistance structured as a second lien, as the lien would need to be repaid or the lender would need to agree to subordinate their loan in order for the borrower to refinance. We thus expect borrowers with secondary financing to be less likely to prepay their mortgages.
[8] We exclude the small proportion of borrowers (about 5 percent) that do not have 30-year amortization terms since finding exact matches for these loans is difficult. We further limit the population to borrowers purchasing one-unit properties, representing 99 percent of the HFA observations in the Fannie Mae dataset. Finally, we exclude borrowers from Puerto Rico for data comparability.
[9] While the majority of HFA-originated mortgages are to first-time homebuyers, we exclude the small subset of mortgages that was not originated to first-time homebuyers (less than 10 percent of HFA originations). The household income threshold of $200,000 is typically higher than the standard 115 percent of the area median income threshold used for most HFA mortgages; however, we wanted to

The Fannie Mae dataset includes details on each loan and borrower at the time of origination and data on loan performance through October 1, 2016. Loan data at the time of origination include the original loan balance and loan terms, the loan to value ratio, indicators for secondary financing, and originator type. Crucially, these data include an indicator for whether or not the loan was financed through an HFA. Borrower data at the time of origination include borrower and co-borrower credit scores, age, income, debt-to-income ratio, and geographic indicators at the ZIP code level. Regarding loan performance, these data include the date of the first 60- or 90-day delinquency and the date of foreclosure or prepayment (if applicable).

To measure variation in HFA service delivery practices, we include data at the state level from the National Council of State Housing Agencies' Annual State HFA Factbook. This Factbook compiles self-reported survey data collected from each of the 56 member agencies yearly regarding agency and program operations. Included in the Factbook are details about the single-family lending programs administered by state HFAs, such as volumes of originated loans, average characteristics of borrowers served, and specific lending practices. We code the Factbook data to identify HFA service delivery practices from 2005 through 2014.[10] Our primary service delivery attributes indicate whether or not the state HFA (in a given year) provides the majority of its loan servicing in-house (versus contracting out servicing to a Master Servicer or other private lenders), whether or not the HFA funded homeownership counseling, and whether or not the HFA administered a refinance program.[11]

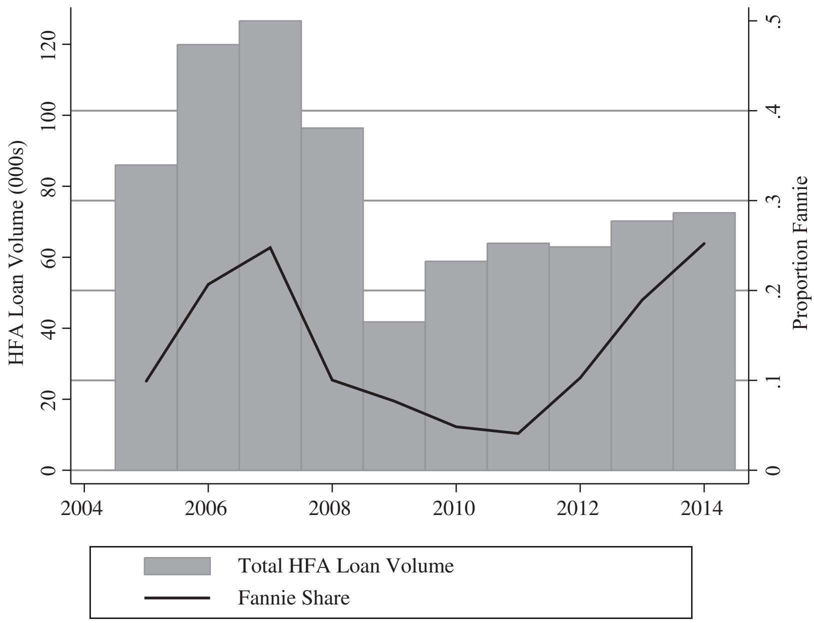
We supplement these datasets with annual data on house prices from the Federal Housing Finance Agency (FHFA) at the ZIP code level (Bogin, Doerner, & Larson 2019), and county level unemployment rates (quarterly) from the Bureau of Labor Statistics. We include the monthly 30-year fixed rate mortgage interest rate from Freddie Mac's Primary Mortgage Market Survey data and the annually adjusted consumer price index from the Organization for Economic Co-operation and Development.

The Fannie Mae dataset includes the universe of HFA originated mortgages securitized through Fannie Mae; however, this represents only a portion of HFA-originated mortgages. The total volume of HFA originations and the proportion securitized by Fannie Mae varies substantially over time in response to changes in the macroeconomy and mortgage environment. Figure 1 plots the proportion of HFA originations securitized by Fannie Mae from 2005 to 2014, relative to the total number of

ensure the ability to identify an appropriate comparison sample for the small subset of HFA borrowers with incomes exceeding the 115 percent threshold (e.g., HFA loans to borrowers in targeted geographies). All HFA loans are full-documentation loans across all time periods, contrasted to 93 percent of non-HFA first-time homebuyer loans from 2005 to 2007. By the last period in the data (2012 to 2014), all loans in the sample population had full documentation. Studies have found substantially higher rates of default found for loans with low or no documentation (Jiang et al., 2014; LaCour-Little, 2009); thus, we restrict our sample to loans with full documentation for comparability. We exclude observations missing data on credit score, loan to value ratio, and monthly loan performance. Because of the size of the files, monthly loan performance data were provided for a random subset comprising 70 percent of the full sample population. We find only minor differences in the observable characteristics such as origination balance, income, and interest rate of those observations with and without missing variables in our analysis.

[10] While we primarily rely on the Factbook data to identify service delivery practices, we validate the information reported in the Factbook with raw data from a survey of state HFAs (Moulton & Quercia, 2014).

[11] We define an HFA as administering a refinance program if they report originating 20 or more loans in a given year for the purposes of refinancing. Using this definition, four HFAs administered refinance programs between 2008 and 2011, increasing to eight HFAs by 2012.



Source: Author's calculations from National Council of State Housing Agency Factbook data and Fannie Mae Single-Family Lending data.
Notes: Total loans include HFA single-family and home purchase loans (excludes refinancing). For the years 2011 through 2014, total loans include other non-MRB single-family loans in addition to MRB loans. Prior to 2010, the total includes only MRB loan volume.

Figure 1. HFA Loan Volume.

HFA single-family originations during the same period per data compiled from the State HFA Factbooks.[12]

The vertical bars indicate the total single-family loan volume across HFAs in a given year. Overall, HFA single-family loan volume spiked in 2007 to a high of nearly 130,000 originations in that year and dropped to a low of about 40,000 originations in 2009. In 2014, total single-family production by HFAs was estimated to be around 73,000 originations (including MRB and other single-family loans, excluding refinancing).[13] The proportion of HFA mortgages that were securitized by Fannie Mae follows a similar trend, making up nearly one-third of HFA originations in 2007, dropping to around 5 percent of HFA originations in 2011, and increasing to nearly 25 percent of originations by 2014. The drop in Fannie Mae volume post the 2008 housing crisis follows trends in the overall market, where Federal Housing Administration (FHA) mortgages dominated the market for first-time homebuyers during that period.

[12] For the years 2011 through 2014, HFA Total Loans include other non-MRB single-family loans in addition to MRB loans. Prior to 2010, the total includes only MRB loan volume, as data on other single-family loans are not reported in the Factbook until 2011 (when non-MRB financing strategies began to grow). Not graphed in Figure 1 are the proportion of HFA mortgages securitized by Fannie Mae or Freddie Mac and those held in an HFA's portfolio.
[13] Volume numbers are derived from the HFA Annual Factbook, and likely undercount non-MRB HFA originations by HFAs. The Factbook data do not report non-MRB loans until 2011, and even then, it is not clear that all non-MRB HFA loans are being reported (e.g., in some recent years, the number of HFA loans in the Fannie Mae database for a particular state exceeds the number reported in the Factbook).

In addition to variation in HFA volume and securitization patterns over time, there is substantial variation in patterns of HFA loans by state. Some state HFAs are more likely to securitize loans through Fannie Mae than others, thus affecting the distribution of loans (by state) in our dataset.[14] Our weighted sample regressions with exact matching on geography, as described below, account for the dominance of particular states with HFA loans in the Fannie Mae database. This helps to ensure that the results are generalizable within the Fannie Mae population of HFA loans.

Sample Construction

In general, HFA borrowers have worse mortgage risk characteristics such as credit score, income, and loan-to-value ratio than non-HFA borrowers, and failing to account for these differences would lead to biased estimates of the HFA effect. To account for these differences, we construct a matched sample of HFA and non-HFA borrowers in the Fannie Mae dataset using a combination of propensity score and exact matching. We follow the approach recommended by Imbens and Rubin (2015) to identify the covariates, interactions among covariates, and higher-order terms to include in the model predicting the propensity to be in the HFA sample. We estimate the propensity score model separately for each of the three cohorts used in our analysis (2005 through 2007; 2008 through 2011; and 2012 through 2014).

Variables used for estimating the propensity score include credit score, household monthly income, debt-to-income (DTI) ratio, and the combined loan-to-value (CLTV) ratio, as well as their interactions and higher order terms as determined appropriate by likelihood ratio tests. We also require exact matching on the following variables: whether or not the loan has a co-borrower, whether or not the loan is originated by a mortgage broker rather than a bank, state of origination, origination year, credit score buckets, and DTI buckets.[15] See the Appendix for a more detailed discussion of our matching procedure.[16]

After estimating a propensity score for each observation, we use nearest neighbor matching without replacement to select the borrowers in the comparison sample who are most similar to each HHF (treated) borrower. This results in a 1:1 match for each HHF and comparison observation. We set a conservative caliper of 0.05, where only those HHF borrowers with a comparison observation's propensity score within 0.05 of the HHF observation's propensity score are included in the final sample. Applying these parameters, we are able to find a match for 70,887 (about 60 percent) of the HHF observations, for a sample size of 141,774.

Borrower and Loan Characteristics for the Matched Sample

To assess the precision of the matching process, we compare the differences in the means of each matching variable between the HFA and non-HFA originations at baseline. Table 1 reports the comparison of means for the unmatched and matched samples. We calculate the standardized difference in means between the HFA and non-HFA observations, with a difference of less than 0.10 indicating good balance

[14] See Appendix Tables A1 and A2 for the distribution of HFA loans in the Fannie Mae database by state and year, relative to the total distribution of HFA loans by state and year. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[15] Credit score is grouped as follows: <620; 620 to 659; 660 to 699; 700 to 739; 740 to 779; and ≥ 780. DTI is grouped as follows: <0.36; 0.36 to 0.44; and ≥ 0.45.

[16] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Table 1. Comparison of HFA vs. non-HFA loan characteristics.

	Unmatched Sample			Matched Sample		
	HFA	Non-HFA	Stand Diff	HFA	Non-HFA	Stand Diff
Monthly Income (000s)	3.74	4.53	−0.446	3.71	3.69	0.013
Debt-to-Income Ratio	0.39	0.40	−0.055	0.40	0.40	0.008
Combined LTV	95.99	90.49	0.498	94.69	94.72	−0.004
Borrower FICO	716.83	720.86	−0.070	710.96	711.08	−0.002
Co-Borrower Indicator	0.28	0.27	0.008	0.25	0.25	0.000
Borrower and Co-Borrower FICO Difference	9.76	7.85	0.089	9.17	7.33	0.083
Origination Balance (000s)	133.42	163.00	−0.375	133.59	128.84	0.074
Borrower Age	32.03	33.99	−0.185	32.00	33.09	−0.106
Single Unit	0.86	0.81	0.129	0.85	0.84	0.028
Broker	0.03	0.19	−0.430	0.03	0.03	0.000
Correspondent	0.54	0.38	0.338	0.46	0.49	−0.061
Community Second	0.26	0.04	0.795	0.15	0.08	0.227
Other Second	0.01	0.07	−0.247	0.01	0.08	−0.312
Interest Rate	5.45	5.70	−0.207	5.62	6.09	−0.475
Direct Servicing	0.32	0.00	1.435	0.24	0.00	0.746
Homeownership Counseling	0.66	0.00	2.118	0.63	0.00	1.359
Refinance Program	0.13	0.00	0.885	0.08	0.00	0.415
Observations	113,984	575,866		70,887	70,887	

Notes: The standardized difference is a test of sample balance after matching, calculated as the difference between the treated and comparison means, divided by the standard deviation for the full matched sample. Variables with standardized differences less than 0.10 are considered to be well balanced (Austin, 2009).

(Austin, 2009).[17] We also compare differences in means for other model variables that will be included as control variables in the regression analysis.

In the unmatched sample, most all variables are unbalanced with standardized differences greater than 0.10. Those in the HFA sample have lower household incomes, lower loan amounts, and higher combined loan-to-value ratios. They are also much less likely to have their loan originated through a broker. By contrast, in the matched sample, only borrower age has a standardized difference greater than 0.10, with HFA borrowers being one year younger on average compared to non-HFA borrowers. We repeat this comparison by origination cohort, and borrower age is the only covariate that differs between the HFA and matched comparison observations.[18]

The sources of secondary financing differ for HFA and non-HFA borrowers, but this is because of how DPA from an HFA is defined. In Fannie Mae's database, DPA provided as a second lien by a nonprofit or public agency such as an HFA is defined as a "community second." Community second liens are subordinate mortgages with favorable financing terms, sometimes requiring no repayment and can be forgiven after a set number of years conditional on successful mortgage performance. In the matched sample, 15 percent of HFA borrowers had community second liens, compared with only 8 percent of non-HFA borrowers. By contrast, 8 percent of non-HFA

[17] The standardized difference is recommended for balance testing after matching, as it is less sensitive to sample size than a t-test. Standardized differences of less than 0.10 indicate good balance (Austin, 2009).

[18] See Appendix Table A3.

borrowers had other types of second liens, compared to only 1 percent of HFA borrowers. In general, secondary financing is associated with higher rates of default (e.g., Demyanyk & Van Hemert, 2011). However, recent studies using Fannie Mae or Federal Housing Finance Agency data that also control for CLTV, debt to income, and cohort effects find a negative relationship between secondary financing and default (Fout, Palim, & Pan, 2020; Leventis, 2014). Table 1 also summarizes whether or not an HFA borrower had a loan from an HFA with a given service delivery practice. In the matched sample, 24 percent of HFA borrowers had loans originated by an HFA providing direct servicing, 63 percent had loans originated by an HFA directly funding homeownership counseling, and 8 percent had loans originated by an HFA offering a refinance program.

A final difference between HFA and non-HFA borrowers, by program design, is the mortgage interest rate. As Table 1 reports, HFA borrower interest rates were 47 basis points below non-HFA borrowers in our matched sample. However, the average subsidy amount changes over the course of our sample period. As Table A3 reports, HFA loans originated between 2005 and 2007 received interest rates that were 67 basis points below their matched non-HFA loans.[19] This subsidy decreased to only 21 basis points for the 2008 to 2011 period and rose to 3 basis points above non-HFA loans for the period 2012 to 2014. Since many HFA loans receive an interest rate subsidy, we do not include it in our matching procedure. We control for the interest rate in our models by calculating the value of the call option in each period, as described below. While the interest rate subsidy has recently disappeared, it will likely rise again after private market interest rates rise (Moulton & Quercia, 2014).

Table 1 indicates that our sample is well balanced on observable covariates used for matching. However, if there are unobserved factors driving borrower selection into an HFA loan that correlate with borrower loan performance, this would bias our estimated HFA effect. According to survey data (Dylla & Caldwell-Tauges, 2012), the primary way that borrowers learn about state HFA loan programs is through their realtor (39 percent) or lender (31 percent); most homeowners were not even aware of HFA loans prior to learning about them from their realtor or lender. Thus, whether or not a borrower receives an HFA loan is in part a function of which realtor or lender they use for their home purchase. To the extent that a borrower's selection of a particular realtor or lender is somewhat random, there is less concern about unobserved selection.

To more directly address the issue of borrower selection based on unobservable characteristics, we implement a coefficient bounding procedure based on Oster (2019). While, by definition, accounting for unobservable variables is not feasible, we can observe how coefficient estimates and the explanatory power of our model change once we account for observable variables. We can then use the following equation to adjust for unobservable selection in our estimates:

$$\beta^* \approx \tilde{\beta} - \delta\left(\beta_0 - \tilde{\beta}\right) * \frac{R_{max} - \tilde{R}}{\tilde{R} - R_0}, \tag{1}$$

where $\beta^*$is our bias-adjusted coefficient estimate. The variables $\tilde{\beta}$ and $\tilde{R}$ are our coefficient estimate and R-squared value when running our model with control variables, β_0 and R_0 are our coefficient estimate and R-squared value running our model without control variables, R_{max} is the maximum possible R-squared value, and δ is the coefficient of proportionality that reflects the assumed relationship between selection on observables relative to selection on unobservables. Assuming a δ value

[19] See Appendix Table A3.

of one means we assume selection on observables is equal to selection on unobservables. Using this equation, we can then calculate two useful parameters: the bias-adjusted HFA coefficient assuming δ is equal to selection on observables, and alternatively, we can derive the minimum δ value needed to bring our HFA coefficient estimate to zero. The other unknown parameter in equation (1) is R_{max}. Typically, this is assumed to be one, meaning that if we could observe every necessary variable, we could perfectly predict mortgage default. We present estimates under varying assumptions about R_{max} in our model.

Methods

We estimate the loan performance of LMI first-time homebuyers in the Fannie Mae database, comparing the performance of HFA-originated mortgages to otherwise similar non-HFA mortgages. As is standard in the mortgage literature, we estimate the competing risks of prepayment and default using a multinomial logit specification (Ding et al., 2011; Pennington-Cross & Chomsisengphet, 2007). The data are constructed as a panel with each borrower-month constituting an observation. The multinomial logit specification restricts the sum of the probabilities of default, prepayment, and remaining active on the loan in each period to one, therefore directly controlling for the competing risks. The likelihood function for the multinomial logit is constructed as:

$$\ln L = \sum_t \sum_i \sum_j d_{ijt}\, ln\, \pi\,(y_{it} = j)$$

$$\pi\,(y_{it} = j) = \frac{e^{\alpha z_{it}}}{1 + \sum_{k=1}^{2} e^{\alpha z_{it}}} \text{ for } j = 1, 2 \tag{2}$$

$$\pi\,(y_{it} = j) = \frac{1}{1 + \sum_{k=1}^{2} e^{\alpha z_{it}}} \text{ for } j = 0,$$

where d_{ijt} is an indicator variable equal to one if outcome j occurs for loan i at time t and zero otherwise, α are the coefficients to be estimated, and z represents the explanatory variables. Our variable of interest is an indicator equal to one if the loan was originated through an HFA. Other explanatory variables include those collected at the time of origination such as FICO credit score, the presence of a co-borrower, the difference in FICO between the borrower and co-borrower, debt-to-income ratio (monthly debt payments divided by income), loan-to-value ratio at origination, borrower age, income, and housing unit type.[20]

Time varying explanatory variables include the calculated value of the call and put options, annual inflation, the quarterly unemployment rate in the county and the time since origination (in months).[21] The call and put options are important

[20] We utilize splines in several of the continuous variables to allow for nonlinearities, including debt-to-income ratio (<36; 36.1 to 45%; >45%) and combined loan-to-value ratio (<60%; 60.1 to 70%; 70.1 to 80%; 80.1 to 90%; and >90%). Testing for nonlinearities in borrower FICO score revealed little evidence of a nonlinear trend.

[21] Fannie Mae data include the mark-to-market LTV for the first mortgage each month, and the combined LTV as of the time of origination. In our primary specifications, we estimate the mark-to-market combined LTV in each month by adding the amount of secondary financing at the time of origination (derived from the combined LTV) to the outstanding mortgage balance each month. In an alternative specification, we calculate the combined LTV excluding the balance on community second liens in the sixth (or more) year after origination, as many community second liens are forgiven after five years. The

variables meant to capture the current period expected financial benefit from either exercising the put option (default, which likely leads to foreclosure) or the call option. The put option is defined as:

$$P_{it} = 100 * \left(\frac{B_{it}}{V_{it}} - 1 \right), \tag{3}$$

where the value of the put option P_{it} is related to the ratio of the current mortgage unpaid balance, B_{it}, to the expected current market value of the home V_{it}. Thus, as the value of the home declines, the value of the put option, or mortgage default, increases.

The call option is defined as:

$$C_{it} = 100 * \left(1 - \frac{R_{it}}{r_{it}} \right), \tag{4}$$

where the value of the call option, C_{it}, is negatively related to the ratio of the value of refinancing given by the predicted market interest rate for individual i at time t, R_{it}, divided by individual i's current mortgage interest rate r_{it}. That is, as the expected mortgage interest rate from refinancing, R_{it}, declines, the value of the call option rises. This reflects the increased financial benefit of replacing the current mortgage rate r_{it} with the borrower's expected market rate R_{it}.[22] An important aspect of the call option is defining R_{it}, the expected market interest rate of refinancing since many HFA borrowers are of lower credit quality and would not qualify for prime mortgage rates. To predict R_{it}, we first estimate the interest rate an HFA borrower would have received at origination, R_{i0}, from a non-HFA lender using our non-HFA sample and regressing origination interest rate on borrower characteristics along with state and quarter fixed effects. We then update R_{it} from R_{i0} using the changes in the prime mortgage rate as reported by the Freddie Mac Monthly Mortgage Survey. All model specifications include origination year and state fixed effects. Standard errors are clustered by borrower. Summary statistics for all model variables, as used in the multinomial logistic regression specification, are included in Table A4.[23]

After estimating our base model, we add controls for structural loan characteristics, including subordinate financing (separating between community second liens and other second liens), and whether or not the loan was originated through a broker or correspondent (vs. bank). In an alternative set of specifications, we add an indicator for the down payment assistance provided as a "gift" to the borrower. The Fannie Mae loan data include the source of down payment assistance for about 40 percent of the observations, and thus our sample for this analysis is limited to those HFA borrowers and their matched comparison observations with data on down payment source.

To explore variation in HFA service delivery practices, we include indicators for whether or not the HFA provided direct servicing in the origination year of an HFA

HFA effects are econometrically and statistically identical to this specification. Results are available from the authors upon request.

[22] Several papers, including Quercia and Spader (2008) and Deng and Gabriel (2006), use an alternative definition of the call option that incorporates the remaining loan term, since refinancing is more valuable as the expected remaining term length increases. Since our sample only consists of 30-year mortgages with an average exposure of four years, incorporating term length would have little effect on our call option variable.

[23] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

loan, whether or not the HFA funded homeownership counseling in the origination year of an HFA loan, and whether or not the state HFA administered a refinance program in the observation year for an HFA loan. Because we include state fixed effects, our specifications measure the effect of within-HFA variation in service delivery practices over time, relative to non-HFA borrowers in the same state.

While our primary specifications estimate the model for the entire sample period, we also estimate subsample regressions for three cohorts of originations corresponding to the pre-crisis (2005 to 2007), crisis (2008 to 2011), and post-crisis (2012 to 2014) periods.

RESULTS

Matched Sample Outcomes: Comparison of Means

The matching process balances the sample of HFA and non-HFA borrowers on observable characteristics. We thus begin by comparing the unconditional means for loan performance outcomes for the HFA and non-HFA matched sample. Table 2 reports differences in loan performance and survival time.

Overall, HFA borrowers have statistically significantly lower rates of 60- and 90-day delinquency and foreclosure than non-HFA borrowers, both during the first 24 months and over the course of the loan. Across all periods, HFA borrowers are less likely to prepay their mortgages than non-HFA borrowers; by the last period in the data (2012 to 2014), this rate of prepayment is half that of other LMI first-time homebuyers (11 percent compared to more than 23 percent prepayment rates for non-HFA borrowers). This may indicate that HFA borrowers are less likely to refinance their loans when it may be “in the money” to do so, either because of lack of information, lower interest rates, transaction costs associated with refinancing, or barriers presented by higher rates of subordinate financing. This is similar to prior research that finds that FHA borrowers have slower prepayment speeds than conventional borrowers (Deng & Gabriel, 2002); however, in this case, both the HFA and non-HFA borrowers have conventional loans securitized by Fannie Mae. The average survival time of HFA borrowers differs from non-HFA borrowers: across all periods, HFA borrowers retain their mortgage for about 12 months longer than otherwise similar non-HFA borrowers.

Figure 2 graphs the unconditional cumulative 90-day default hazard for HFA and non-HFA borrowers, showing that the gap in the default hazard between HFA and non-HFA borrowers is persistent over time. This is important, as it suggests that the HFA effect is not simply the result of a temporary delay that deteriorates over time.

Multinomial Logit Results of Competing Risks

Table 3 presents the normalized marginal effects from the multinomial logit regression that models that risk of 90-day default or foreclosure relative to prepayment.[24] Because the probability of default or prepayment in any given month is very small, we normalize the marginal effects by the outcome mean for each model, which are shown at the bottom of each table. The normalized marginal effects can be interpreted as the percent change in the probability of an outcome in a given period.

The HFA indicator reveals a large negative association with the risk of default or foreclosure. Specifically, the risk of default is 29 percent lower and the risk of

[24] We also estimated a similar model predicting 60-day rather than 90-day default. The results are similar to the 90-day results and are available from the authors upon request.

Table 2. Comparison of outcomes, matched sample.

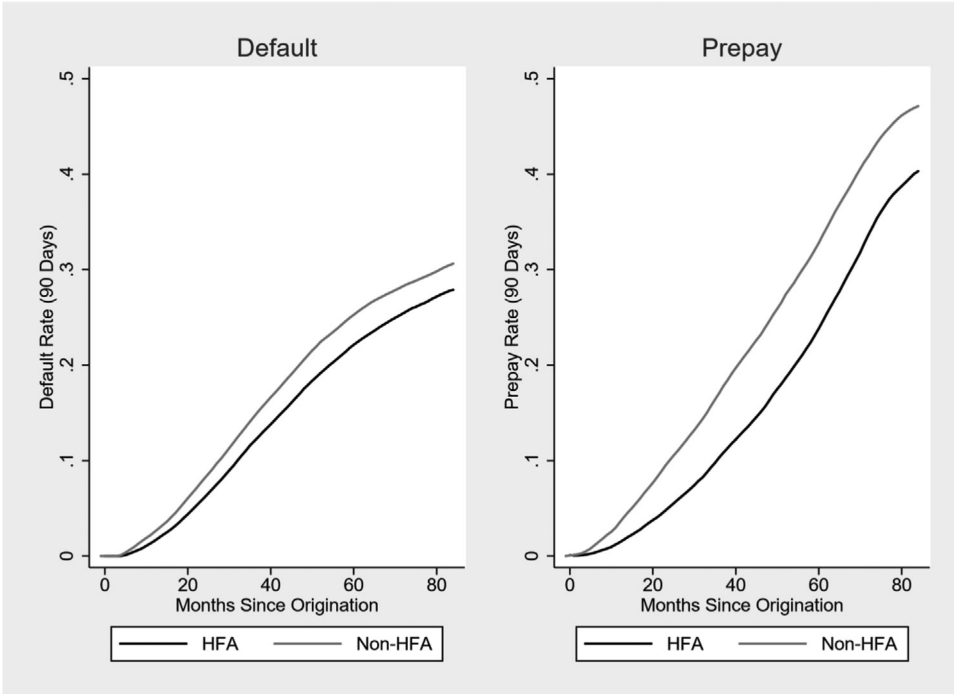
	All Periods		2005-2007		2008-2011		2012-2014	
	HFA	Non-HFA	HFA	Non-HFA	HFA	Non-HFA	HFA	Non-HFA
60 Days Delinquent (24 months)	0.084	0.105	0.110	0.138	0.062	0.077	0.009	0.009
	(0.278)	(0.306)	(0.313)	(0.344)	(0.242)	(0.267)	(0.096)	(0.093)
90 Days Delinquent (24 months)	0.061	0.081	0.079	0.106	0.047	0.063	0.005	0.005
	(0.239)	(0.272)	(0.270)	(0.307)	(0.212)	(0.243)	(0.070)	(0.071)
60 Days Delinquent (Ever)	0.252	0.267	0.338	0.359	0.160	0.161	0.013	0.017
	(0.434)	(0.442)	(0.473)	(0.480)	(0.367)	(0.368)	(0.113)	(0.131)
90 Days Delinquent (Ever)	0.227	0.246	0.307	0.334	0.138	0.143	0.008	0.011
	(0.419)	(0.431)	(0.461)	(0.471)	(0.345)	(0.350)	(0.087)	(0.102)
Foreclosure (Ever)	0.127	0.155	0.177	0.215	0.056	0.068	0.001	0.001
	(0.333)	(0.361)	(0.382)	(0.411)	(0.231)	(0.252)	(0.027)	(0.031)
Prepay (Ever)	0.450	0.524	0.528	0.584	0.553	0.655	0.111	0.230
	(0.497)	(0.499)	(0.499)	(0.493)	(0.497)	(0.475)	(0.314)	(0.421)
Number of Periods Alive	60.645	52.507	67.208	56.650	57.683	50.260	39.782	39.583
	(33.838)	(32.179)	(36.429)	(35.548)	(28.76)	(28.57)	(11.38)	(12.47)
Observations	70,887	70,887	48,103	48,103	8,916	8,916	13,868	13,868

Notes: All differences between HFA and non-HFA loans are statistically significant at $p<0.05$ with the exception of 60 and 90 days delinquent (ever) for the 2008 to 2011 cohort and 60 and 90 days delinquent (24 months) and foreclosure (ever) for the 2012 to 2014 cohort.

Table 3. Competing risk of default, foreclosure, or prepayment.

	Competing Risk of Default		Competing Risk of Foreclosure	
	Default	Prepay	Foreclose	Prepay
HFA	−0.2867***	−0.2125***	−0.3242***	−0.1592***
	(0.014)	(0.008)	(0.017)	(0.008)
Put Option Value	0.0074***	−0.0057***	0.0074***	−0.0098***
	(0.000)	(0.000)	(0.000)	(0.000)
Call Option Value	−0.0010	0.0235***	0.0013	0.0247***
	(0.001)	(0.000)	(0.001)	(0.000)
Inflation	−0.0787***	−0.1022***	−0.0130*	−0.0956***
	(0.004)	(0.003)	(0.005)	(0.003)
Unemployment Rate	0.0565***	−0.0724***	0.0387***	−0.0675***
	(0.003)	(0.002)	(0.004)	(0.002)
Exposure Months	0.0001***	0.0004***	0.0001***	0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Exposure Months (Squared)	−0.0000***	−0.0000***	−0.0000***	−0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)
Monthly Income (000s)	−0.1780***	0.1033***	−0.0962***	0.1215***
	(0.008)	(0.005)	(0.011)	(0.005)
DTI$\leq$ 36	0.0081***	0.0061***	0.0060**	0.0063***
	(0.002)	(0.001)	(0.002)	(0.001)
36 $<$ DTI $\leq$ 45	0.0091***	0.0062***	0.0076***	0.0064***
	(0.001)	(0.001)	(0.002)	(0.001)
DTI $>$ 45	0.0080***	0.0045***	0.0070***	0.0043***
	(0.001)	(0.001)	(0.001)	(0.001)
Combined LTV $\leq$ 60	0.0179***	−0.0090***	0.0277***	−0.0075**
	(0.005)	(0.002)	(0.007)	(0.002)
60 $<$ CLTV $\leq$ 70	0.0155***	−0.0067***	0.0284***	−0.0049**
	(0.004)	(0.002)	(0.006)	(0.002)
70 $<$ CLTV $\leq$ 80	0.0121***	−0.0047**	0.0263***	−0.0026
	(0.003)	(0.001)	(0.005)	(0.001)
80 $<$ CLTV $\leq$ 90	0.0121***	−0.0054***	0.0262***	−0.0033*
	(0.003)	(0.001)	(0.004)	(0.001)
CLTV $>$ 90	0.0157***	−0.0059***	0.0286***	−0.0040***
	(0.003)	(0.001)	(0.004)	(0.001)
Borrower FICO	−0.0111***	0.0024***	−0.0066***	0.0036***
	(0.000)	(0.000)	(0.000)	(0.000)
Co-Borrower Indicator	0.0489**	−0.0032	−0.0233	−0.0124
	(0.018)	(0.012)	(0.023)	(0.012)
Borrower and Co-Borrower FICO Difference	−0.0018***	−0.0002	−0.0006	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Origination Balance (000s)	0.0051***	0.0028***	0.0027***	0.0020***
	(0.000)	(0.000)	(0.000)	(0.000)
Borrower Age	0.0048***	−0.0167***	−0.0037***	−0.0175***
	(0.001)	(0.000)	(0.001)	(0.000)
Missing Borrower Age	−0.0830**	0.0079	−0.0998**	0.0251
	(0.027)	(0.018)	(0.036)	(0.017)
Single Unit	−0.0129	0.1062***	−0.2003***	0.0626***
	(0.017)	(0.012)	(0.020)	(0.012)
Observations	7,862,095	7,862,095	9,154,776	9,154,776
Monthly Outcome Rate	0.0043	0.0087	0.0022	0.0078

Notes: All estimates are normalized marginal effects from the multinomial logit panel regression, interpreted as the percent change in a given outcome. Robust standard errors, clustered by borrower, are in parentheses. All models include state and year fixed effects.
*$p<0.05$; **$p<0.01$; ***$p<0.001$.



Source: Fannie Mae loan performance data.

Figure 2. Cumulative Hazard Rate of Default.

foreclosure is 32 percent lower for observably similar HFA borrowers compared to non-HFA borrowers. The relative risk of prepayment is 21 and 16 percent lower, respectively. The coefficients for the put and call options follow expectations, with the put option increasing the relative risk of default and reducing the risk of prepayment, and the call option increasing the risk of prepayment and not affecting default. Other model covariates have the expected signs, where borrowers with higher incomes, higher credit scores, and co-borrowers are less likely to default or foreclose, and those with higher debt-to-income ratios are more likely to default or foreclose.

Why are HFA-originated loans associated with lower rates of default? To inform this question, we add to our model structural loan characteristics as well as service delivery attributes that vary within HFAs over time. Table 4 reports the normalized marginal effects for these models for all origination years. All other variables (not shown) included in the base specification (see Table 3) are also included in the regressions, in addition to state and year fixed effects.

The models with structural characteristics of the loan include whether or not the loan was originated through a broker or correspondent channel, and the presence of sub-financing (community second or other second lien). Mortgages originated through brokers or correspondents, as opposed to in-house origination, have a higher risk of default and are less likely to prepay. This finding is in line with prior literature that finds that third-party originated mortgages have a higher risk of default (Alexander et al., 2002; Ding et al., 2011; Jiang, Nelson, & Vytlacil, 2014; Moulton, 2010; Stegman et al., 2007).

Table 4. Competing risk of default, structural and service delivery variables.

	Base Model		Structural		Service Delivery	
	Default	Prepay	Default	Prepay	Default	Prepay
HFA	−0.2867***	−0.2125***	−0.2546***	−0.2169***	−0.1800***	−0.2010***
	(0.014)	(0.008)	(0.015)	(0.009)	(0.020)	(0.014)
Broker			0.1579***	−0.0718**	0.1565***	−0.0836**
			(0.032)	(0.026)	(0.032)	(0.026)
Correspondent			0.0996***	−0.0545***	0.0974***	−0.0530***
			(0.014)	(0.009)	(0.014)	(0.009)
Community Second			−0.0674**	−0.2457***	−0.0625**	−0.2421***
			(0.021)	(0.014)	(0.022)	(0.014)
Other Second			0.0419	−0.1366***	0.043	−0.1391***
			(0.029)	(0.017)	(0.029)	(0.017)
Direct Servicing					−0.2804***	−0.2212***
					(0.035)	(0.020)
Homeownership Counseling					−0.0729***	0.0447**
					(0.021)	(0.014)
Refinance Program					0.1211*	0.0723**
					(0.052)	(0.026)
Observations	7,862,095	7,862,095	7,862,095	7,862,095	7,862,095	7,862,095
Monthly Outcome Rate	0.0043	0.0087	0.0043	0.0087	0.0043	0.0087

Table 4. Continued.

	Base Model		Structural		Service Delivery	
	Foreclose	Prepay	Foreclose	Prepay	Foreclose	Prepay
HFA	−0.3242***	−0.1592***	−0.2903***	−0.1674***	−0.2208***	−0.1581***
	(0.017)	(0.008)	(0.018)	(0.008)	(0.024)	(0.013)
Broker			0.0441	−0.1042***	0.0456	−0.1136***
			(0.041)	(0.025)	(0.041)	(0.025)
Correspondent			0.0628***	−0.0751***	0.0643***	−0.0735***
			(0.017)	(0.009)	(0.017)	(0.009)
Community Second			−0.1638***	−0.2660***	−0.1633***	−0.2640***
			(0.027)	(0.014)	(0.027)	(0.014)
Other Second			−0.02	−0.1703***	−0.016	−0.1730***
			(0.036)	(0.017)	(0.036)	(0.017)
Direct Servicing					−0.1240*	−0.1940***
					(0.049)	(0.020)
Homeownership Counseling					−0.0973***	0.0469***
					(0.027)	(0.014)
Refinance Program					0.0298	0.0536*
					(0.066)	(0.026)
Observations	9,154,776	9,154,776	9,154,776	9,154,776	9,154,776	9,154,776
Monthly Outcome Rate	0.0022	0.0078	0.0022	0.0078	0.0022	0.0078

Notes: All estimates are normalized marginal effects from the multinomial logit panel regression, interpreted as the percent change in a given outcome. Robust standard errors, clustered by borrower, are in parentheses. All models include covariates in Table 3, including state and year fixed effects.
*p < 0.05; **p < 0.01; ***p < 0.001.

Loans with community seconds are associated with a 7 percent reduced risk of default and a 16 percent reduced risk of foreclosure, while those with other second liens are not significantly more or less likely to default or foreclose. This finding contrasts with other studies that have found higher rates of default among loans with secondary financing (e.g., Demyanyk & Van Hemert, 2011). However, this finding is consistent with recent studies using Fannie Mae or FHFA data that also control for CLTV, debt to income, and cohort effects (Fout, Palim, & Pan, 2020; Leventis, 2014). Because community second liens are affordable secondary financing from a public or nonprofit source, a lower probability of default with this form of secondary financing may be due to subsidized interest rates or eventual principal forgiveness.[25]

To further probe the relationship between down payment assistance and default, we estimate an alternative specification that restricts our analysis sample to those observations with the source of down payment specified in the Fannie Mae dataset. This limits the sample to 26,034 unique borrowers. In addition to accounting for down payment assistance structured as a community second and presence of other second liens, we construct an indicator for down payment assistance structured as a gift.[26] Here, self-funded down payment becomes the reference category. In this specification, borrowers with down payment assistance structured as a gift are 14 percent more likely to default than those with self-funded down payments. Down payment assistance structured as a community second lien is still negative but no longer statistically significant, relative to those with self-funded down payments.

Table 4 also reports results from the models including HFA service delivery practices. Recall that the service delivery practices are only coded “1” for HFA originations with a given practice, and “0” for all other HFA originations and all non-HFA loans. These results may thus be interpreted as within-HFA variation in servicing practices. Direct servicing of loans by the HFA in a given year is associated with a reduction in the relative default and foreclosure risk of about 28 percent and 12 percent, respectively, and a significant reduction in the likelihood of prepayment. Loans originated by HFAs that directly fund homeownership counseling in a given year are associated with a 7 percent reduction in the risk of default and a 10 percent reduction in the risk of foreclosure. Funding homeownership counseling is positively associated with the likelihood of prepayment; counseling may increase homeowner information about when and how to refinance.

Finally, we observe that borrowers with loans from an HFA that operates a refinance program are significantly more likely to prepay their mortgage in the year the refinance program is in operation, relative to other HFA borrowers. While we cannot observe the reason for prepayment in our data, this finding is noteworthy given that prepayment rates are considerably lower for HFA borrowers than for non-HFA borrowers. HFAs that offer refinance programs directly may reduce barriers to refinancing for HFA loans. The results also indicate that borrowers from HFAs with a refinance program in operation are more likely to default, but not significantly more likely to foreclose. One interpretation of this association is that HFAs that offer refinance programs do so as a tool to mitigate foreclosure when a borrower experiences default.

Using within-HFA variation over time, the structural loan covariates and HFA service delivery practices explain 37 percent of the lower risk of default for HFA-originated mortgages and 32 percent of the lower risk of foreclosure. By

[25] See https://www.fanniemae.com/content/fact_sheet/community-seconds-fact-sheet.pdf.
[26] We code as gift sources of down payment that are categorized as gift funds, as well as other sources that exclude any type of funds from the borrower (e.g., cash, checking or savings, retirement funds, proceeds from closing) as well as unsecured or secured debt financing.

contrast, the structural covariates and service delivery practices explain only about 1 percent of the difference in prepayment. Our identification strategy relies on within-state HFA variation in service delivery practices over time; the inclusion of state and HFA fixed effects hold constant time invariant differences between HFAs that are correlated with default. However, if there are other unmeasured time varying factors or HFA policies that are correlated with changes in these service delivery practices, our results may overstate the causal effect of these policies.

To supplement our quantitative estimates, we merge our analysis dataset with qualitative survey data on state HFA service delivery practices collected in 2012 as part of a separate study (Moulton & Quercia, 2014). Specifically, 20 HFAs responded to the survey in 2012 and appear in our dataset. Eight of these respondents reported directly servicing their loans in 2012. The HFAs with direct servicing describe a streamlined approach to servicing their loans and getting borrowers help when needed. For example, one HFA describes their strategy this way: "We have one point of contact for the borrower, always have, so they can get all their options reviewed by one counselor. And we provide financial counseling to help borrowers stay in their home." The agencies with direct servicing also describe a more hands-on, personalized approach. One HFA indicates: "We attempt contact with a 30-day delinquent borrower three times by month end, both mail and phone; we have many additional contact attempts both verbal and in writing above and beyond FHA requirements." Those HFAs providing direct servicing are also more likely to report referring their borrowers to delinquency counseling to prevent foreclosure (75 percent compared with 56 percent of those not engaged in direct servicing).

Table 5 presents the HFA estimates by origination cohort for our three different model specifications. The results from the first row indicate that the significance and magnitude of the HFA effect on default is strong and persistent over time across cohorts in our base specification.[27] This finding eliminates concerns that our primary results might be driven by any single cohort and provides evidence of a longstanding performance advantage for HFA loans. Rows 2 and 3 in Table 5 report the HFA effect from models that add the structural characteristics (row 2) and HFA service delivery practices (row 3). The HFA effect remains strongly negatively associated with default and foreclosure and of a similar magnitude across cohorts and specifications. Only in the third period (2012 to 2014) is the HFA effect on foreclosure not statistically significant in the base specification; however, the foreclosure rate in the third period is near zero percent, reducing our power to detect an effect and we cannot reject the hypothesis that the third period foreclosure effect is the same as the first period or the second period. With regard to prepayment, the HFA effect is statistically robust and grows over time, from 14 percent to 29 percent to 88 percent less likely to prepay across cohorts in the base specification when competing with default risk.

To inform the issue of selection on unobservable characteristics, we compute a bias-adjusted HFA effect, β^{*}, and a minimum δ value using equation (1) from Oster (2019). To do so, we must use a linear probability model, predicting the probability of default in each month. In the base model without controls we find an HFA effect of $\beta 0 = -.0066$ and adding controls this effect grows to $\tilde{\beta} = -0.00741$.[28] The base

[27] The HFA effect on foreclosure is not statistically significant in the third period (2012 to 2014); however, the base probability of a loan in the third cohort ever foreclosing by the end of the study period is less than 1 percent, reducing the power to detect an effect.
[28] All specifications include year and state fixed effects; we do not expect differential HFA selection to be based on these variables.

Table 5. Competing risks, compare HFA effect by origination cohort.

Panel A: Competing Risk of Default

	2005–2007		2008-2011		2012-2014	
	Default	Prepay	Default	Prepay	Default	Prepay
HFA (Base)	−0.2986***	−0.1351***	−0.2402***	−0.2837***	−0.2660*	−0.8825***
	(0.015)	(0.010)	(0.044)	(0.021)	(0.132)	(0.036)
HFA (Structural)	−0.2621***	−0.1474***	−0.2159***	−0.2524***	−0.4255**	−0.8988***
	(0.016)	(0.011)	(0.047)	(0.022)	(0.161)	(0.042)
HFA (Servicing)	−0.1829***	−0.1780***	−0.3091**	−0.3453***	−0.3414	−0.7717***
	(0.021)	(0.016)	(0.119)	(0.058)	(0.292)	(0.076)
Observations	5,828,182	5,828,182	950,013	950,013	1,083,900	1,083,900
Monthly Outcome Rate	0.0054	0.0091	0.0027	0.0113	0.0023	0.0044

Panel B: Competing Risk of Foreclosure

	2005–2007		2008-2011		2012-2014	
	Foreclose	Prepay	Foreclose	Prepay	Foreclose	Prepay
HFA (Base)	−0.3234***	−0.0521***	−0.3509***	−0.2781***	−0.1809	−0.8788***
	(0.018)	(0.010)	(0.064)	(0.020)	(0.420)	(0.036)
HFA (Structural)	−0.2886***	−0.0701***	−0.3088***	−0.2468***	−0.2199	−0.8910***
	(0.019)	(0.011)	(0.066)	(0.022)	(0.505)	(0.042)
HFA (Servicing)	−0.2302***	−0.1116***	−0.203	−0.3153***	−0.1470	−0.7566***
	(0.025)	(0.016)	(0.159)	(0.057)	(0.823)	(0.076)
Observations	7,016,324	7,016,324	1,050,285	1,050,285	1,088,167	1,088,167
Monthly Outcome Rate	0.0027	0.0079	0.0011	0.0105	0.0002	0.0044

Notes: All estimates are normalized marginal effects from the multinomial logit panel regression, interpreted as the percent change in a given outcome. Robust standard errors, clustered by borrower, are in parentheses. All models include covariates in Table 3, including state and year fixed effects.
*p < 0.05; **p < 0.01; ***p < 0.001.

default probability in a given month of 3.3 percentage points implies an HFA effect of 22 percent default reduction, similar to our multinomial logit results. Because the HFA effect grows as controls are included, this suggests borrowers negatively select into HFA loans (e.g., those who are more likely to default are also more likely to select an HFA loan). Assuming a maximum R-squared value of $R_{max} = 1$, this implies a bias-adjusted HFA effect of $\beta^{*}= -2.895$ when $\delta = 1$ and alternatively implies a δ value of -0.32 is needed to bring β^{*} equal to zero. Assuming a more reasonable maximum R-squared value of $R_{max} = 0.2$ alters our bias-adjusted HFA effect to $\beta^{*} = -0.01556$ when $\delta = 1$ and a δ value of -2.015 is needed to bring β^{*} equal to zero. This δ value implies that selection on unobservable characteristics would need to be both twice as strong as selection on observables to bring our HFA effect to zero and that selection on unobservables moves in the opposite direction of selection on observables. We interpret this test as strong evidence that unobserved selection is unlikely to be driving our results.

Robustness Tests

We estimate several alternative specifications to probe the robustness of our results. Results of the robustness tests are available in the Appendix.[29] First, rather than treating the outcome as the competing risk of default or prepayment using multinomial logit (MNL) panel estimation, we model only the hazard of default using a Cox proportional hazard model. The HFA effect estimated with the hazard model is very similar to the estimates from the MNL specification; HFA originations are associated with a 24 percent reduction in the risk of default in the base specification, decreasing to 21 and 13 percent reductions in default risk after including structural loan characteristics and service delivery variables, respectively. The size and significance of the origination and service delivery variables are also similar to the estimates from the MNL specification.

The concentration of the Fannie Mae share of HFA mortgage originations varies considerably across states. To validate that our HFA effect is not driven by any single state we first rerun our baseline specification 51 times, dropping all borrowers from a single state each time. We find that our HFA default effect ranges between -0.297 to -0.271 and the HFA prepayment effect ranges between -0.244 to -0.200. We further identify borrowers from the five states with the greatest number of Fannie Mae HFA originations—Ohio, Nebraska, Florida, Massachusetts, and Iowa—and re-run our baseline specification separately for borrowers in each of these states. The results all confirm a large and statistically significant HFA effect on mortgage default, ranging from -0.17 to -0.42. It is unsurprising that the HFA effect varies across states as each state HFA is operated independently and can vary across many dimensions; however, the consistent large reduction in default among HFA loans across states helps validate our baseline findings.

Our primary specifications represent average effects for HFA loans in Fannie Mae's portfolio. As an alternative specification, we re-weight our data to represent the distribution of HFA loans in the population by state and year. This reduces the influence of some of the states that have a disproportionate share of HFA volume in the Fannie Mae dataset, increasing the generalizability of the results to the HFA population as a whole. Re-weighting reduces the magnitude of the HFA on default from -0.29 in the base model to -0.20. The reduction in the risk of prepayment remains the same, at -0.21 in the base model and in the HFA population weighted specification.

CONCLUSIONS

Our empirical results indicate HFAs reduce the risk of mortgage default and foreclosure to low- and moderate-income first-time homebuyers by 30 percent. This effect is consistent across origination cohorts and model specifications. This is a large improvement in mortgage performance, equivalent to the default reduction resulting from reducing mortgage payments by nearly a third. We estimate that 37 percent of this effect is related to differences in HFA service delivery practices, as well as structural differences between HFA and non-HFA loans. Lower risks of prepayment among HFA-originated mortgages are persistent across origination cohorts.

The findings from this study contribute to an understanding of different ways to reduce the risk of lending to LMI first-time homebuyers, beyond stricter screening at origination. Our results suggest two pathways through which policy may intervene

[29] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

to reduce default risk: improving service delivery practices of lender servicers and changing structural characteristics of affordable mortgages. State HFAs provide an ideal context to explore these pathways, as there is substantial between- and within-state variation during our sample period.

First, our results provide novel evidence that variation in service delivery practices contribute to improved loan outcomes for LMI borrowers. This is critical given the shifting landscape of mortgage lending infrastructure toward becoming less personalized (Fuster et al., 2019; Jagtiani, Lambie-Hanson, & Lambie-Hanson, 2019). For LMI borrowers, higher touch strategies contribute to reduced risk of default and foreclosure. Our qualitative evidence suggests that these strategies are more likely to be employed by lenders directly servicing their loans, rather than those contracting out servicing. Direct servicing could be particularly beneficial for public lenders as public entities are more inclined to consider the negative externalities stemming from foreclosure. Streamlined contact with delinquent borrowers may increase information exchange and facilitate loss mitigation strategies such as mortgage modifications. This highlights the benefits that come from aligning incentives of lenders (in this case, the public agency) and servicers (in this case, private mortgage servicers) to enable preventative servicing while protecting the servicer (e.g., from investors).

While we find this in the context of mortgage lending, our findings contribute to a broader literature on contracting in the delivery of public programs (Amirkhanyan, Kim, & Lambright, 2008; Amirkhanyan et al., 2018; Bel & Rosell, 2016; Marvel & Marvel, 2007). Our findings provide evidence that direct public delivery of services can provide public benefits that may not be valued (or incentivized) in the private market. While other studies have examined the benefit of direct provision in other contexts such as municipal services (Bel & Rosell, 2016; Marvel & Marvel, 2007) or healthcare (Amirkhanyan, Kim, & Lambright, 2008; Amirkhanyan et al., 2018), ours is the first known study to document the benefit of direct government service provision in the context of mortgage lending.

Second, our findings point to specific structural characteristics of mortgages that can be manipulated to reduce the risk of default. Most basically, the lower interest rate on HFA loans reduces the monthly payment, thereby increasing affordability and lowering default risk. Our estimate of the average interest rate subsidy for HFA loans in our sample is 47 basis points, which corresponds to an expected 5.5 percent reduction in mortgage default based on estimates derived by Fuster and Willen (2017). Thus, the interest rate subsidy alone can only explain a small portion of our observed HFA effect.

We also find evidence that the structure of down payment assistance is associated with default risk. Specifically, borrowers with down payment assistance structured as a community second lien are significantly less likely to default than borrowers who finance their down payments in other ways. In an alternative specification, we find that those with community seconds are no more likely to default than borrowers who self-fund their down payments. By contrast, borrowers who use gift funds for their down payments are more likely to default. These findings have important implications for policy, as lack of money for down payment is consistently the most significant barrier to purchasing a home for LMI households. There are more than 2,500 local, state, and federal government programs that provide down payment assistance (Goodman et al., 2017). Many of these programs structure their assistance as a community second lien that may or may not require repayment. Prior studies offer mixed results about whether or not having "skin in the game" is necessary to reduce the risk of default (Freeman & Harden, 2015; Kelly, 2008; Stacy, Theodos, & Bai, 2018), and subsequently, if down payment assistance increases the risk of default. Our study cautions against generalizing from these findings without identifying the source and structure of assistance.

Another explanation for the HFA effect on default could be borrower selection, as unobserved variables, such as household persistence or stability, could contribute to loan performance. However, we show that unobserved variables are unlikely to be driving our HFA effect since this effect grows in magnitude if we assume that selection on observed variables, such as income and credit score, is similar to selection based on unobserved variables. Further, we show that selection on unobserved variables would need to be twice as large and in the opposite direction as selection on our observed variables in order for our HFA effect on default to disappear.

While these results are informative, there are limitations. A primary assumption of ours requiring further investigation is that HFA lending does not affect the extensive margin of mortgage origination. If in the absence of HFA lending, HFA borrowers would not have entered homeownership, an appropriate control group of private market borrowers may not exist. Ideally, we would also have data on the universe of first-time LMI homebuyers, allowing us to better model HFA selection. Notably, by limiting our sample to Fannie Mae loans, we are missing data on FHA and subprime loans. Future research incorporating these loans is needed to help identify possible selection effects.

Taken together, our results suggest that HFA lending reduces mortgage default and foreclosure among first-time LMI borrowers. HFAs operate quite differently from private lenders to this population on many dimensions, so disentangling all the components of this HFA effect is challenging. We provide evidence that 37 percent of the reduced mortgage default of HFA originations can be attributed to structural loan characteristics and service delivery practices. These findings have important implications for strategies to increase the sustainability of homeownership for low- and moderate-income households, beyond restricting access through underwriting. More broadly, these findings highlight the critical role that public entities can play in the delivery of services—even those, such as mortgage lending, that are traditionally provided through the private market.

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APPENDIX

HFA TOTAL LOAN VOLUME BY STATE AND YEAR

Table A1 shows the total number of HFA loans originated by state and year.

FANNIE MAE HFA LOAN VOLUME BY STATE AND YEAR

The Fannie Mae dataset includes only a portion of total HFA loans. The proportion of HFA loans securitized by Fannie Mae varies by state and over time. Table A2 shows the number of HFA loans securitized by Fannie Mae for the state and year. The Fannie Mae share of HFA originations in a state and year can be calculated by dividing the number of Fannie Mae HFA loans in Table A2 for a state and year by the number of total HFA loans by state and year in Table A1. Several states emerge as dominant HFA lenders in the sample in different time periods. Prior to 2009, states with a large share of HFA mortgages securitized by Fannie Mae include Florida, Ohio, Iowa, and Illinois, although many states were represented in the Fannie Mae HFA database. After 2009, fewer states securitized a large portion of their loans through Fannie Mae, with Massachusetts emerging as the most dominant originator.

MATCHING PROCEDURE

We use a combination of propensity score matching and coarsened exact matching to construct our matched sample. First, we estimate the propensity for a borrower to be in the HFA sample following the approach recommended by Imbens and Rubin (2015). We use STATA's "psestimate" command to identify second order covariates among our specified list of first order covariates (FICO, income, DTI, and LTV). The coefficients are estimated through logistic regression using maximum likelihood. The psestimate algorithm uses a step-wise approach to add interactions and higher order terms one at a time to the base model. If the added covariate contributes a significant amount of explanatory power to the model (as indicated by the likelihood ratio test), the covariate is included in the model. The psestimate algorithm continues this process iteratively until no remaining likelihood ratio tests are statistically significant. After identifying the set of covariates to include in the probability model, the propensity score is estimated (separately for each cohort), resulting in a new variable indicating the predicted probability of being in the HFA sample corresponding to each borrower.

To enable exact matching on particular covariates, we create a new group indicator that numerically assigns a value greater than one to each unique combination of borrowers on our specified set of variables. Specifically, we group observations on the following indicators: whether or not the loan has a co-borrower, broker origination, state of origination, origination year, FICO buckets, and DTI buckets. FICO is grouped as follows: < 620; 620 to 659; 660 to 699; 700 to 739; 740 to 779; and ≥ 780.

DTI is grouped as follows: < 0.36; 0.36 to 0.44; ≥ 0.45.

We then add together the new group numeric indicator (value greater than one) with the estimated propensity score (value less than one) and use nearest neighbor matching without replacement to select the borrowers in the comparison sample who are most similar to each HHF (treated) borrower. This results in a 1:1 match for each HHF and comparison observation. We set a conservative caliper of 0.05, where only those HHF borrowers with a comparison observation's propensity score within 0.05 of the HHF observation's propensity score are included in the final sample.

Table A1. HFA total loan volume by state and year.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AK	942	1,328	1,403	1,383	302	2,078	1,305	1,082	1,850	1,650
AL	0	695	2,167	657	0	0	998	892	782	0
AR	0	1,085	1,331	1,272	269	513	593	599	540	335
AZ	116	280	366	156	6	108	368	132	207	461
CA	5,327	6,140	5,217	4,070	168	7	1,394	0	0	0
CO	2,390	2,422	2,934	2,816	203	0	2,337	2,135	2,415	1,664
CT	3,558	4,010	0	2,794	1,976	1,963	1,612	1,445	1,733	2,333
DC	0	150	273	31	0	36	44	0	54	216
DE	394	1,089	2,117	1,281	525	626	876	407	737	475
FL	1,163	2,723	4,704	3,390	2,578	4,369	3,712	2,784	2,036	2,800
GA	447	1,125	1,381	987	449	1,118	1,417	1,005	1,465	1,226
HI	13	90	29	0	0	0	0	22	107	0
IA	2,487	3,006	3,681	2,047	672	1,100	1,013	2,102	1,402	0
ID	1,230	1,734	4,098	2,199	289	207	2,750	5,075	3,842	4,798
IL	1,662	1,647	0	1,089	17	311	1,002	1,697	0	8,313
IN	1,682	2,430	2,691	2,997	507	1,082	1,269	1,549	1,196	1,694
KY	3,803	5,221	4,095	2,582	1,751	2,069	1,030	442	2,449	1,999
LA	428	1,556	2,080	1,609	437	444	505	95	208	282
MA	896	1,341	1,263	1,183	744	836	1,137	3,041	4,110	3,263
MD	887	2,591	4,064	2,340	702	707	1,595	1,731	1,799	1,399
ME	1,019	1,094	961	1,163	1,002	916	795	318	610	482
MI	1,150	2,396	2,014	4,426	899	947	1,099	0	0	1,364
MN	2,845	2,784	3,683	2,419	935	2,287	2,320	2,403	3,329	2,872
MO	2,409	3,407	3,078	1,482	1,644	2,818	3,308	4,470	4,801	1,114
MS	1,749	2,700	2,982	859	198	587	621	495	6	164
MT	1,822	1,758	1,751	778	255	0	270	0	568	368
NC	1,445	2,173	3,185	1,266	280	317	478	730	1,232	1,693
ND	1,249	1,324	1,662	1,656	1,620	1,388	1,110	885	1,072	936
NE	1,542	3,688	4,766	2,182	424	1,585	1,504	1,150	2,219	1,949
NH	1,212	1,228	1,380	759	421	527	613	495	689	903
NJ	483	1,159	2,163	1,780	728	579	777	693	1,132	583
NM	1,058	1,901	2,311	1,760	1,417	1,159	1,012	895	1,147	1,098
NV	0	222	0	495	218	553	0	0	56	698
NY	3,206	3,399	2,672	4,001	1,136	2,240	1,683	797	1,717	991
OH	5,027	9,918	7,965	7,038	2,296	3,234	3,448	3,342	3,871	1,622
OK	1,281	2,155	1,845	751	787	1,122	1,213	1,441	586	830
OR	1,195	1,171	1,381	1,598	381	37	620	434	419	382
PA	5,678	6,660	6,960	4,839	2,905	6,527	4,361	3,076	1,656	3,036
RI	838	1,088	1,449	928	718	409	354	425	484	820
SC	802	1,852	1,489	1,286	535	1,043	706	365	298	288
SD	2,245	2,495	2,792	2,432	1,730	1,700	1,447	808	1,486	1,149
TN	2,431	3,270	4,647	2,885	2,446	2,650	2,222	2,240	2,071	1,695
TX	1,924	2,531	2,636	1,409	273	1,248	1,920	2,100	1,827	1,413
UT	1,991	2,030	2,193	1,915	959	1,130	1,852	2,686	2,685	3,323
VA	5,114	6,166	5,348	4,954	3,964	3,409	2,445	3,422	3,771	3,981
VT	707	935	993	495	95	135	221	407	360	221
WA	1,004	1,755	1,870	794	684	1,370	1,124	489	2,753	3,150
WI	4,131	4,559	4,705	2,748	0	700	374	651	1,126	1,246
WV	1,473	1,488	1,564	897	252	0	450	851	581	466
WY	1,563	1,951	2,272	1,547	1,016	690	662	633	754	798

Table A2. Fannie Mae HFA volume by state and year.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AK	1	0	0	0	0	2	0	0	0	1
AL	2	142	1,026	157	0	0	0	0	28	661
AR	26	141	301	90	0	0	0	0	0	2
AZ	114	199	51	2	0	0	0	0	0	1
CA	27	59	1,236	248	13	7	57	44	43	130
CO	6	72	140	92	0	0	0	4	545	735
CT	0	0	0	0	0	0	0	0	91	344
DC	1	123	27	6	0	0	0	0	41	156
DE	247	795	1,305	318	0	27	50	43	54	52
FL	413	1,838	3,369	905	113	51	19	13	82	767
GA	54	201	475	99	2	1	1	0	0	0
HI	41	38	29	0	0	0	0	30	78	0
IA	1,317	2,122	2,352	614	127	127	171	282	546	358
ID	3	10	626	1,168	403	286	180	970	1,403	1,178
IL	115	346	1,210	15	0	0	182	260	963	3,977
IN	194	721	176	510	4	4	11	7	16	110
KS	82	468	0	0	0	0	0	0	0	0
KY	797	2,005	1,445	82	15	0	0	0	427	601
LA	95	631	63	4	35	8	2	3	17	8
MA	109	295	825	729	1,896	1,180	884	2,647	2,958	1,772
MD	6	14	1	0	0	0	0	17	283	359
ME	0	0	0	0	0	0	0	0	0	0
MI	0	0	0	0	0	0	0	0	0	0
MN	284	501	150	0	42	210	127	293	889	855
MO	351	1,129	969	175	59	10	42	25	27	67
MS	5	269	1,162	134	0	0	1	1	0	20
MT	7	17	15	31	8	0	0	0	0	0
NC	0	0	0	0	0	0	0	0	0	372
ND	0	1	0	0	0	0	0	0	0	0
NE	435	2,598	3,745	884	0	0	88	80	671	719
NH	0	0	0	0	0	0	3	25	114	208
NJ	0	0	0	0	0	0	0	0	0	0
NM	134	696	1,179	474	100	59	112	145	237	260
NV	3	65	169	64	0	2	0	0	4	69
NY	0	0	0	0	0	0	0	0	4	42
OH	1,285	6,338	5,594	1,811	23	51	129	97	388	137
OK	308	655	767	24	0	0	0	0	0	4
OR	0	0	0	0	0	0	0	0	0	13
PA	1,040	654	118	251	2	0	19	461	1,174	1,112
RI	0	0	0	0	0	0	0	101	197	206
SC	0	0	0	0	0	0	0	0	0	7
SD	27	6	0	0	0	0	0	84	244	233
TN	0	0	0	0	0	0	0	0	0	0
TX	348	1,062	1,234	73	2	14	15	0	0	12
UT	192	233	250	294	111	0	0	0	203	584
VA	0	1	0	0	1	0	0	80	325	304
VT	0	0	0	0	33	18	66	115	105	56
WA	528	658	1,292	381	141	96	76	57	351	973
WI	0	149	0	0	15	671	369	586	969	999
WV	16	11	62	41	73	24	14	47	34	29
WY	0	0	0	0	0	0	0	30	118	114

Table A3. Comparison of HFA vs. non-HFA loan characteristics by cohort, unmatched sample.

	2005–2007			2008–2011			2012–2014		
	HFA	Non-HFA	Stand Diff	HFA	Non-HFA	Stand Diff	HFA	Non-HFA	Stand Diff
Monthly Income (000s)	3.29	4.10	−0.504	3.97	4.61	−0.354	4.37	5.13	−0.416
Debt-to-Income Ratio	0.41	0.44	−0.171	0.39	0.39	−0.005	0.35	0.34	0.109
Combined LTV	95.96	94.32	0.160	94.69	85.20	0.785	96.61	87.17	0.927
Borrower FICO	701.91	694.98	0.115	727.43	742.11	−0.319	737.00	749.87	−0.331
Co-Borrower Indicator	0.26	0.26	0.002	0.29	0.24	0.110	0.29	0.30	−0.021
FICO Difference	9.46	7.52	0.087	9.70	5.74	0.217	10.27	9.30	0.046
Origination Balance	119.40	146.70	−0.391	143.26	173.43	−0.356	152.40	182.63	−0.362
Borrower Age	31.74	33.99	−0.209	32.50	34.61	−0.195	32.29	33.69	−0.137
Missing Borrower Age	0.01	0.07	−0.246	0.01	0.12	−0.378	0.00	0.02	−0.141
Single Unit	0.88	0.83	0.132	0.80	0.76	0.094	0.85	0.80	0.132
Broker	0.04	0.27	−0.549	0.04	0.17	−0.384	0.02	0.09	−0.246
Correspondent	0.27	0.40	−0.275	0.67	0.37	0.599	0.95	0.34	1.216
Community Second	0.13	0.07	0.203	0.24	0.02	1.016	0.48	0.01	1.672
Other Second	0.01	0.11	−0.329	0.01	0.03	−0.156	0.00	0.02	−0.129
Interest Rate	5.98	6.66	−1.102	5.63	5.68	−0.064	4.51	4.27	0.487
Direct Servicing	0.15	0.00	0.941	0.48	0.00	1.834	0.54	0.00	1.933
Homeownership Counseling	0.66	0.00	2.081	0.66	0.00	2.192	0.65	0.00	2.147
Observations	61,103	291,847		16,112	88,656		36,770	195,363	

Table A3. Continued.

	2005–2007			2008–2011			2012–2014		
	HFA	Non-HFA	Stand Diff	HFA	Non-HFA	Stand Diff	HFA	Non-HFA	Stand Diff
Monthly Income (000s)	3.40	3.37	0.032	4.00	4.14	−0.086	4.57	4.51	0.034
Debt-to-Income Ratio	0.42	0.42	0.005	0.39	0.39	0.023	0.35	0.35	0.008
Combined LTV	95.88	96.00	−0.014	91.52	91.69	−0.017	92.61	92.25	0.046
Borrower FICO	698.57	698.96	−0.007	729.25	729.41	−0.003	742.18	741.36	0.020
Co-Borrower Indicator	0.25	0.25	0.000	0.25	0.25	0.000	0.26	0.26	0.000
FICO Difference	9.13	7.30	0.081	8.53	6.21	0.115	9.76	8.16	0.075
Origination Balance	123.25	117.95	0.097	145.31	146.85	−0.021	161.91	155.06	0.090
Borrower Age	31.89	32.97	−0.103	32.61	33.51	−0.087	31.96	33.23	−0.132
Missing Borrower Age	0.02	0.09	−0.336	0.01	0.13	−0.492	0.00	0.03	−0.229
Single Unit	0.87	0.86	0.033	0.78	0.80	−0.039	0.82	0.80	0.061
Broker	0.04	0.04	0.000	0.03	0.03	0.000	0.01	0.01	0.000
Correspondent	0.27	0.52	−0.520	0.68	0.42	0.511	0.96	0.40	1.206
Community Second	0.12	0.09	0.114	0.16	0.05	0.386	0.24	0.07	0.478
Other Second	0.02	0.10	−0.357	0.01	0.05	−0.237	0.00	0.02	−0.158
Interest Rate	5.99	6.66	−1.114	5.64	5.85	−0.261	4.33	4.30	0.064
Direct Servicing	0.15	0.00	0.562	0.38	0.00	0.969	0.50	0.00	1.151
Homeownership Counseling	0.63	0.00	1.360	0.68	0.00	1.436	0.60	0.00	1.308
Observations	48,103	48,103		8,916	8,916		13,868	13,868	

Notes: The standardized difference is a test of sample balance after matching, calculated as the difference between the treated and comparison means, divided by the standard deviation for the full matched sample. Variables with standardized differences less than 0.10 are considered to be well balanced (Austin, 2009).

Table A4. MNL model variables, descriptive statistics.

	All	Non-HFA	HFA
Monthly Income (000s)	3.56	3.57	3.56
	(1.35)	(1.41)	(1.29)
DTI$\leq$ 36	10.66	10.80	10.54
	(14.29)	(14.29)	(14.28)
36 $<$ DTI $\leq$ 45	13.54	13.54	13.54
	(19.18)	(19.17)	(19.19)
DTI $>$ 45	15.72	15.35	16.04
	(24.49)	(24.27)	(24.68)
Combined LTV $\leq$ 60	0.61	0.66	0.57
	(5.48)	(5.63)	(5.35)
60 $<$ CLTV $\leq$ 70	0.87	0.76	0.98
	(7.57)	(7.07)	(8.00)
70 $<$ CLTV $\leq$ 80	7.97	8.14	7.82
	(23.79)	(24.05)	(23.56)
80 $<$ CLTV $\leq$ 90	7.37	7.33	7.41
	(24.45)	(24.48)	(24.43)
CLTV $>$ 90	77.88	77.80	77.95
	(40.25)	(40.25)	(40.25)
Borrower FICO	712.13	713.16	711.21
	(55.86)	(55.34)	(56.29)
Co-Borrower Indicator	0.24	0.24	0.24
	(0.43)	(0.43)	(0.43)
Borrower and Co-Borrower FICO Difference	8.13	7.11	9.03
	(22.18)	(20.53)	(23.50)
Origination Balance (000s)	123.84	121.24	126.15
	(59.90)	(60.66)	(59.13)
Borrower Age	32.84	33.34	32.40
	(10.44)	(10.88)	(10.01)
Missing Borrower Age	0.05	0.09	0.01
	(0.22)	(0.29)	(0.12)
Single Unit	0.84	0.83	0.85
	(0.36)	(0.37)	(0.36)
Broker	0.03	0.03	0.03
	(0.17)	(0.17)	(0.17)
Correspondent	0.43	0.47	0.40
	(0.50)	(0.50)	(0.49)
Community Second	0.12	0.09	0.15
	(0.32)	(0.28)	(0.36)
Other Second	0.05	0.09	0.02
	(0.22)	(0.28)	(0.13)
Direct Servicing	0.12	0.00	0.22
	(0.32)	0.00	(0.41)
Homeownership Counseling	0.34	0.00	0.63
	(0.47)	0.00	(0.48)
Refinance Program	0.05	0.00	0.09
	(0.21)	0.00	(0.28)
Put Option Value	−5.99	−6.90	−5.19
	(23.19)	(23.65)	(22.74)
Call Option Value	11.59	14.81	8.74
	(17.69)	(15.81)	(18.74)
Inflation	1.93	1.98	1.89
	(1.60)	(1.62)	(1.59)
Unemployment Rate	6.58	6.56	6.60
	(2.54)	(2.57)	(2.51)
Exposure Months	39.27	36.91	41.35
	(29.62)	(28.77)	(30.19)

Table A4. Continued.

	All	Non-HFA	HFA
Exposure Months (Squared)	2,418.98	2,190.01	2,621.68
	(3,325.27)	(3,155.45)	(3,456.03)
Observations	7,862,102	3,691,851	4,170,251

Table A5. Cox proportional hazard model, 90 day default.

	Base	Structural	Service
HFA	−0.2390***	−0.2094***	−0.1251***
	(0.014)	(0.014)	(0.019)
Put Option Value	0.0079***	0.0077***	0.0078***
	0.000	0.000	0.000
Call Option Value	0.0048***	0.0046***	0.0051***
	(0.001)	(0.001)	(0.001)
Inflation	−0.0398***	−0.0399***	−0.0392***
	(0.004)	(0.004)	(0.004)
Unemployment Rate	0.0527***	0.0536***	0.0543***
	(0.003)	(0.003)	(0.003)
Monthly Income (000s)	−0.1789***	−0.1793***	−0.1775***
	(0.008)	(0.008)	(0.008)
DTI$\leq$ 36	0.0084***	0.0081***	0.0077***
	(0.002)	(0.002)	(0.002)
$36 < \text{DTI} \leq 45$	0.0094***	0.0092***	0.0089***
	(0.001)	(0.001)	(0.001)
DTI $>$ 45	0.0083***	0.0080***	0.0078***
	(0.001)	(0.001)	(0.001)
Combined LTV $\leq$ 60	0.0194***	0.0235***	0.0241***
	(0.005)	(0.005)	(0.005)
$60 < \text{CLTV} \leq 70$	0.0167***	0.0200***	0.0204***
	(0.004)	(0.004)	(0.004)
$70 < \text{CLTV} \leq 80$	0.0131***	0.0159***	0.0162***
	(0.003)	(0.003)	(0.003)
$80 < \text{CLTV} \leq 90$	0.0129***	0.0154***	0.0157***
	(0.003)	(0.003)	(0.003)
CLTV $>$ 90	0.0165***	0.0188***	0.0190***
	(0.002)	(0.002)	(0.003)
Borrower FICO	−0.0115***	−0.0114***	−0.0114***
	0.000	0.000	0.000
Co-Borrower Indicator	0.0433*	0.0431*	0.0389*
	(0.018)	(0.018)	(0.018)
FICO Difference	−0.0018***	−0.0017***	−0.0016***
	0.000	0.000	0.000
Origination Balance (000s)	0.0050***	0.0049***	0.0049***
	0.000	0.000	0.000
Borrower Age	0.0048***	0.0048***	0.0048***
	(0.001)	(0.001)	(0.001)
Missing Borrower Age	−0.0841**	−0.0954***	−0.0660*
	(0.027)	(0.028)	(0.027)
Single Unit	−0.0042	−0.0033	−0.0052
	(0.016)	(0.016)	(0.016)

Table A5. Continued.

	Base	Structural	Service
Broker		0.1566***	0.1540***
		(0.030)	(0.030)
Correspondent		0.0920***	0.0894***
		(0.013)	(0.013)
Community Second		−0.0596**	−0.0532**
		(0.020)	(0.020)
Other Second		0.0505	0.0509
		(0.029)	(0.029)
Direct Servicing			−0.3425***
			(0.036)
Homeownership Counseling			−0.0768***
			(0.020)
Refinance Program			0.1519***
			(0.053)
Observations	7,853,668	7,853,668	7,853,668

*p < 0.05; **p < 0.01; ***p < 0.001.

Table A6. Competing risks of default, by state.

	Ohio		Nebraska	
	Default	Prepay	Default	Prepay
HFA	−0.2583***	−0.0693***	−0.4188***	−0.1285***
	(0.033)	(0.020)	(0.083)	(0.037)
Observations	1,735,010	1,735,010	335,485	335,485
	Massachusetts		**Iowa**	
	Default	Prepay	Default	Prepay
HFA	−0.3641***	−0.4583***	−0.2254***	0.0256
	(0.070)	(0.029)	(0.053)	(0.025)
Observations	591,202	591,202	651,424	651,424
	Florida			
HFA	Default	Prepay		
HFA	−0.1721***	−0.3155***		
	(0.032)	(0.043)		
Observations	626,401	626,401		

*p < 0.05; **p < 0.01; ***p < 0.001.

Table A7. Competing risks, weight by national HFA volume.

	Default	Prepay
HFA	−0.1966***	−0.2130***
	(0.029)	(0.019)
Observations	7,612,512	7,612,512

*p < 0.05; **p < 0.01; ***p < 0.001.
Note: Estimated using the Base model specification.