Expanding Mortgage Credit: The FHLB System's Impact on Small-Dollar Lending, Credit Risk, and Securitization Decisions

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March 2024

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Abstract

This paper studies the effects of the Federal Home Loan Bank (FHLB) system mortgage finance programs on mortgage originators' lending behavior. Through the Mortgage Purchase Program (MPP) and Mortgage Partnership Finance (MPF), the FHLBs offer member institutions an additional secondary market financing outlet for mortgages that uniquely rewards mortgage lenders through additional income on high performing loans while holding lenders responsible for any credit losses on mortgages they sell. I provide evidence that take-up of MPP and MPF is higher among lenders who originate more small-dollar mortgages and that use of these programs leads to statistically significant increases in both total and small-dollar mortgage lending by as much as 33%. This increase represents an equilibrium result driven by simultaneous expansions in credit demand through mortgage applications and credit supply through loan approvals. Moreover, I document that these increases accrue mainly to borrowers of lower credit risk. Lastly, I show that use of Fannie Mae and Freddie Mac mortgage credit decline for lenders participating in the FHLB mortgage finance programs, suggesting that these lenders may find the FHLB programs to be a cheaper source of credit through a combination of more competitive pricing and the absence of guarantee fees despite the retention of credit risk. In particular, this decline in Fannie Mae and Freddie Mac credit is highest for loans in medium and high risk pools, suggesting that participating lenders may prefer retaining the credit risk on these classes of mortgages for the opportunity to earn additional income in the event that they perform over paying the steeper associated guarantee fees.

*I thank my advisors Winnie van Dijk and Cameron LaPoint for their support, guidance, and mentorship as I undertook this project. I also thank Sarah Clark, Larry Lauger, and many others at the Federal Home Loan Bank of Cincinnati for their support during my time with the bank as well as over the past year.

1 Introduction

Over $1 trillion in mortgage loans are originated in the U.S. annually. Roughly 60%-70% of these mortgages are sold on the secondary market, which refers to the marketplace in which investors purchase mortgages from lenders by paying an amount roughly equal to the size of the underlying loan in return for the claim to the majority of the anticipated interest payments. In addition to removing risk from lenders' balance sheets associated with investing in mortgages, this greatly expands the pool of credit available for financing residential mortgages in the primary market by liquidating mortgage lenders' balance sheets (Loutskina (2011)). However, shortcomings in the primary and secondary mortgage markets still exist. Recent research has noted that despite the availability of secondary market credit, small-dollar mortgages, which are loans worth less than or equal to $100,000 and which offer financially underserved communities a pathway to homeownership, remain inaccessible (Amornsiripanitch and Ricks (2024); Goldstein and DeMaria (2022); Horowitz and Roche (2023)). Furthermore, sale of mortgages on the secondary market is costly and requires mortgage lenders to pay upfront fees which are subsequently passed on to consumers originating the loans. Finally, the sale of mortgages on the secondary market can lead to more lenient applicant screening requirements and riskier lending practices because mortgage lenders are no longer responsible for the risks associated with these mortgages (Richardson et al. (2017)). Therefore, understanding how the structure of secondary market credit affects mortgage originators' lending behavior is an important issue.

This paper studies the effects of the Federal Home Loan Bank (FHLB) mortgage finance programs, a source of secondary market credit established in the early 2000's which has not been studied in academic literature, on mortgage originators' lending decisions. The FHLB mortgage finance programs differ from the credit offered by the largest secondary market investors, government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac, in that unlike these GSEs which assume the credit risk associated with the mortgages they purchase in exchange for a non-refundable guarantee fee, lenders remain responsible for the credit risk associated with the mortgages they sell to the

FHLBs. This allows lenders selling to the FHLB mortgage finance programs to recuperate income on performing loans, or loans where the borrower is making payments on time and in full, that would otherwise be lost on guarantee fees paid to Fannie Mae and Freddie Mac and also incentivizes lenders to only originate loans of high credit quality. I study both the effectiveness of the FHLB mortgage finance programs in expanding mortgage credit for its users as well as the ways in which the programs help mitigate the shortcomings of secondary market credit noted above.

Data is a key challenge in studying these programs and may account for their absence in the literature. I rely on data published by the Federal Housing Finance Agency (FHFA) on all mortgages sold to the FHLBs from 2009-2023 to identify lenders who use the programs as well as Home Mortgage Disclosure Act (HMDA) data to link these lenders to their mortgage market outcomes. However, I face several identification challenges. Because I only observe the lender associated with each mortgage sold to the FHLBs from 2009-2014, I ultimately restrict my sample to lenders who adopt the program in these years. While I demonstrate that lenders in my sample are statistically and economically similar to earlier and later adopters of the FHLB programs, this may limit the generalizibility of my findings. I also face selection bias in program take-up and moreover from the fact that some lenders who initially adopt the programs do not continue to use them for long enough periods to observe full treatment outcomes. Furthermore, heterogeneity in the timing of program adoption means that the treatment and control groups do not remain stable over time. I address these issues by deploying Callaway and Sant'Anna (2021)'s difference-in-differences (DiD) estimator for staggered treatment timing using the not-yet-treated lenders as my control group, restricting my sample to lenders who use the programs for at least four years. This early versus late design helps to create balance on observables that predict program participation, which I provide support for by showing that observable properties of different adoption year cohorts are statistically similar in terms of financial and geographic composition. Nevertheless, this research design also may reduce the external generalizability of my results.

I begin my analysis by showing that these programs are popular among the FHLB member institutions who serve borrowers with lower incomes relative to the median income in their census tracts and who originate larger shares of small-dollar mortgages, which I define as loans worth less than or equal to $100,000 (Goldstein and DeMaria (2022)) and are considered to be pathways to homeownership for financially underserved communities (Horowitz and Roche (2023)). This may be because these lenders find the FHLB mortgage finance programs, through either more competitive prices, additional income offered on performing loans and the absence of guarantee fees, or a combination thereof, to be a cheaper source of secondary market credit than Fannie Mae or Freddie Mac, which may be of particular importance for these lenders since small-dollar and low-income mortgages tend to be less profitable given the fixed costs of originating a mortgage (Horowitz and Roche (2023); Amornsiripanitch et al. (2024)). I show that participation in the FHLB mortgage finance programs increases both total and small-dollar mortgage lending in equilibrium by as much as 33%, a statistically significant result. Moreover, using loan-to-income (LTI) ratios grouped by year and by census tract as a proxy for borrower creditworthiness (Ganong and Noel (2023)), I show that mortgage lending increases primarily among low and medium-risk borrowers while no significant increases accrue to high-risk borrowers. This suggests that by holding lenders responsible for the credit risk on loans they sell to the programs, the FHLB mortgage finance programs do not increase risky lending.

I next turn my analysis to studying how participation in MPP and MPF affects mortgage application outcomes to understand whether the equilibrium lending increases following participation in the FHLB programs is driven primarily by increased supply, demand, or some combination thereof. Controlling for borrower observables, I do not find convincing evidence that these programs increase the likelihood of mortgage application approval. Rather, I find that increases in lending are primarily driven by an increase in mortgage application volumes, suggesting that increases in lending following use of MPP and MPF are driven not only by increased lending capacity through additional credit from the FHLBs but also by increased demand from borrowers. This could be the result of a variety of factors including lower interest rates, lower application fees, or increased capacity to accept and approve applications. However, given these findings, it is unlikely that the increases in lending result from relaxed screening criteria.

Finally, I analyze how participation in the FHLB mortgage finance programs affect mortgage securitization decisions. I find no evidence that these programs reduce the volume of loans which lenders retain on their balance sheets, suggesting that lenders continue to hold and earn income on originated loans to the extent for which they have capacity. However, I do find that lenders use MPP and MPF as a substitute for securitization through Fannie Mae and Freddie Mac, with statistically significant results suggesting as high as 50% declines in the use of GSE credit. This provides further support for the claim that participating lenders, likely through a combination of more competitive prices and additional income earned on performing loans, find FHLB credit to be cheaper than that of Fannie Mae and Freddie Mac. I also find that this substitution effect is strongest for medium and high-risk loans as measured by LTI, suggesting that lenders prefer retaining the credit risk on these loans with the potential to earn additional income through the FHLB mortgage finance programs rather than paying the steeper guarantee fees associated with them.

One limitation of my analysis is that I do not observe the prices paid to mortgage originators on loans purchased by Fannie Mae and Freddie Mac nor the FHLBs. When secondary market investors purchase mortgages from lenders, they pay a sum proportional to the size of the underlying loan; for example, a price of 102% paid by an investor for a mortgage of $100,000 on the secondary market means that the investor paid the lender of the mortgage $102,000 for the claim to the anticipated principal and interest installments on that mortgage. Thus, when I observe that lenders demonstrate a preference for the FHLB mortgage finance programs over Fannie Mae and Freddie Mac or that the FHLB mortgage finance programs are popular among small-dollar mortgage lenders, I cannot observe whether this is because the FHLBs offer more competitive prices or because of the additional income lenders anticipate earning on performing loans. However, these two factors are related given that earning additional income on performing loans is equivalent to paying a lower upfront price. With data on pricing offered by both investors, by observing lenders' securitization decisions, I could quantify lenders' preferences for paying guarantee fees versus retaining credit risk on the mortgages they sell. However, because I do not observe prices paid, I can only infer that when a lender chooses to sell loans through the FHLB mortgage finance programs as opposed to Fannie Mae and Freddie Mac, it is due to a combination of competitive pricing and the absence of guarantee fees.

The rest of this paper is organized as follows. Section 2 reviews the literature and outlines my contribution. Section 3 discusses relevant details regarding the secondary mortgage market and the FHLB mortgage finance programs. Section 4 presents my conceptual framework and outlines my empirical predictions. Section 5 describes the data that I use. Section 6 explains how I construct my sample and provides support for my identification strategy. Section 7 presents my findings, and Section 8 concludes.

2 Literature Review

This paper contributes to two strands of literature. I begin by discussing how it contributes to the large literature on the effects of secondary market credit on mortgage lending. I address three subliteratures within this literature.

First, I add to the subliterature focused on how secondary market credit expands mortgage lending (Ambrose and Thibodeau (2004); Frame and White (2005); Loutskina and Strahan (2009); Loutskina (2011)). There is significant research documenting that secondary market credit increases mortgage lending by providing additional sources of funding and liquidity to banks, making them less sensitive to funding shocks and illiquidity. Furthermore, Passmore and Sherlund (2021) show that access to government mortgage programs such as Fannie Mae and Freddie Mac stabilizes mortgage credit access during financial downturns. I add to these findings by documenting that another government-sponsored lending program, specifically the FHLB mortgage finance programs, significantly increase mortgage lending for local and regional lenders who are more likely to serve lower income households and who originate a larger share of small-dollar mortgages.

Second, I contribute to the subliterature focused on the effects of costs associated with secondary market credit on mortgage lenders' behavior. Alexandrov et al. (2022), Ahsin (2024), Kalda et al. (2024), and Amornsiripanitch and Ricks (2024) all analyze how mortgage lenders respond to changes in guarantee fees charged by Fannie Mae and Freddie Mac, two large mortgage securitizers, on loans they purchase in the secondary market. All four find that securitization costs are passed on to the borrowing consumers. I contribute to these findings by studying how lenders' securitization decisions change in response to the introduction of a potentially cheaper form of secondary mortgage credit, specifically that of the FHLB mortgage finance programs. I document that some lenders demonstrate a preference for FHLB mortgage credit over Fannie Mae and Freddie Mac credit, which suggests that these lenders find the FHLB mortgage finance programs to offer an overall cheaper source of mortgage credit. This is likely due to more competitive pricing, the absence of guarantee fees, or some combination thereof.

Third, I address the subliterature focused on the effects of secondary market credit on risky mortgage lending. Lu and Yu (2020) argue that Fannie Mae and Freddie Mac mortgage purchases had negative effects on mortgage originators' screening incentives prior to the financial crisis. Richardson et al. (2017) argue that by guaranteeing all mortgages they purchase, Fannie Mae and Freddie Mac encourage excess risk-taking in mortgage lending. Similarly, Elenev et al. (2016) argue that by underpricing guarantee fees, Fannie Mae and Freddie Mac contribute to riskier mortgage originations. Amornsiripanitch et al. (2024) note that, despite the US Treasury reducing their exposure to speculative mortgages in 2021, Fannie Mae and Freddie Mac still invest in non-speculative mortgages from high risk borrowers. Gete and Zecchetto (2018) analyze via a model the removal of Fannie Mae and Freddie Mac credit guarantees and find that while foreclosures fall, low- and mid-income households suffer. I add to this literature by demonstrating that through their unique risk-sharing structure in which lenders retain credit risk on mortgages they sell, the FHLB mortgage finance programs increase mortgage lenders' origination volumes primarily for borrowers with low and medium loan-to-income (LTI) ratios, thereby incentivizing lenders to increase lending without doing so for risky borrowers.

The second literature to which I contribute is a growing literature on small-dollar mortgages. These loans are often manufactured homes which constitute the largest source unsubsidized affordable housing in the US (Doerr and Fuster (2025)) and offer financially underserved communities a pathway to homeownership (Horowitz and Roche (2023)). Recent research has documented that borrowers seeking to obtain small-dollar mortgages face substantial barriers in the form of higher rejection probabilities, higher interest rates, and higher fees (Brevoort (2022); Goldstein and DeMaria (2022)). One proposed explanation for this which has been supported by empirical evidence is low profitability due to high fixed costs associated with originating a mortgage (Horowitz and Roche (2023); Amornsiripanitch and Ricks (2024)). I add support to this explanation by documenting that MPP and MPF, which provide local and regional lenders with a secondary market credit source that offers potentially greater profitability than traditional secondary market outlets, is popular among small-dollar lenders and significantly increases small-dollar mortgage origination volumes.

3 Institutional Background

3.1 Residential Mortgage Finance

In this section, I provide background information on the secondary mortgage market and introduce its main investors. Upon mortgage origination, lenders are exposed to two different kinds of risks. First, they face credit risk which bears on whether the borrower will repay the borrowed amount and the agreed upon interest. Second, they face market risk which refers to the possibility of changes in market conditions, primarily interest rates, affecting the value of the mortgage. Lengthy maturities, fixed interest rates, and prepayment options make the value of mortgage debt sensitive to changes in interest rates. Rising interest rates mean that lenders will be collecting a fixed rate on existing mortgages that is lower than the current market rate, while average maturities of nearly 30 years mean that these losses can be extended for long periods of time, especially because borrowers are less likely to prepay their mortgages if they are paying an effectively discounted rate. Conversely, if interest rates fall, because borrowers will now be paying a premium compared to the current market rate, prepayment is more likely, depriving lenders of interest that would otherwise be accrued over the life of the loan.

The main way lenders protect themselves from the risk associated with mortgage origination is through sale of mortgage loans on the secondary market. Each year, over 60% of mortgage originations are sold to investors on the secondary market, while lenders retain the remainder of the loans on their balance sheets. The main secondary market investors are the Federal National Mortgage Association (FNMA, or 'Fannie Mae') and the Federal Home Loan Mortgage Corporation (FHLMC, or 'Freddie Mac'), which are government-sponsored enterprises (GSEs) created by Congress to provide liquidity, stability, and affordability to the mortgage market.[1] After purchasing mortgage loans from lenders, Fannie Mae and Freddie Mac package and sell these loans to investors as mortgage backed securities ('agency MBS'), providing the investors with guarantees to the cash flows in the event of default. It is important to note that the sale of mortgages to Fannie Mae and Freddie Mac is costly. In return for the credit guarantees offered on agency MBS, Fannie Mae and Freddie Mac charge mortgage lenders guarantee fees, or 'g-fees', which are paid in terms of percentages of the volume of the underlying mortgage.

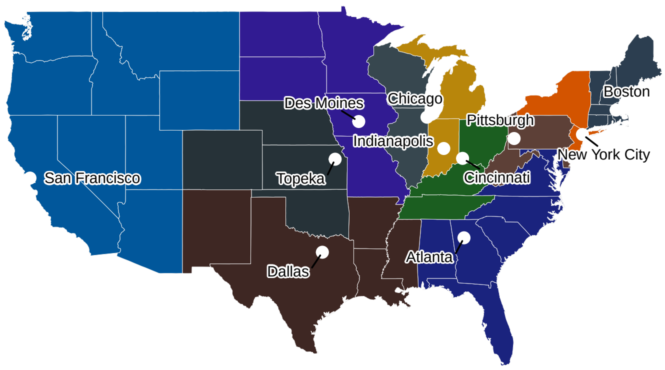
3.2 Federal Home Loan Bank Mortgage Finance Programs

I now introduce the Federal Home Loan Bank (FHLB) system and discuss the details of its mortgage finance programs. The FHLBs are eleven regional banks established in 1932 that, as a whole, constitute a single government-sponsored enterprise created specifically to fulfill the joint mission of providing liquidity to its members in order to support housing finance and community development as well as to support affordable housing (FHLBanks (2025)). One of the many ways the FHLBs fulfill this mission is by providing mortgage liquidity to their member institutions through their mortgage finance programs. Financial institutions eligible for FHLB membership include thrift institu-

[1] I exclude the Government National Mortgage Association (GNMA, or 'Ginnie Mae') from my discussion as Ginnie Mae only purchases government-guaranteed loans which are not relevant to my discussion. I also exclude mention of private-label securitizers due to very little use of private-label credit among users of the FHLB mortgage finance programs.

tions, commercial banks, credit unions, insurance companies, and certified community development financial institutions which, in addition to other regulatory requirements, make long-term home mortgages and have at least 10% of their total assets in residential mortgage loans. Each financial institution is only eligible to join and interact with the FHLB in the district that serves the state where the institution's principal place of business is located. In Figure 1, I display a map of the distribution of the FHLBs and their corresponding districts.

Figure 1: Geographic Distribution of the FHLBs and Their Districts



Note: This mpa plots the geographic distribution of the eleven FHLBs and their corresponding districts.

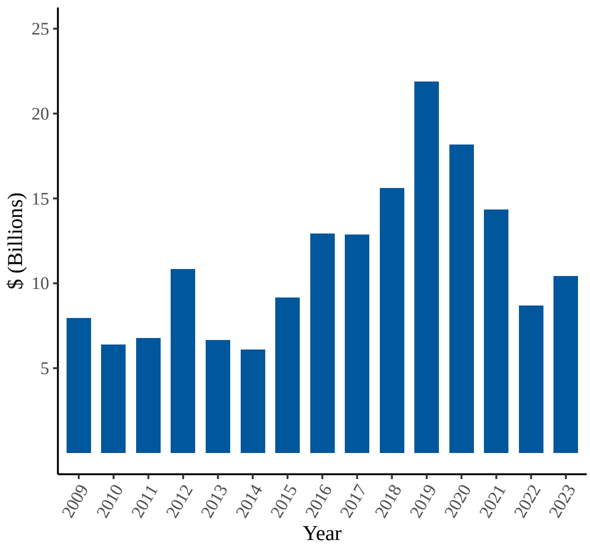
In the late 1990's and early 2000's, each FHLB introduced a mortgage finance program to offer an additional secondary market credit outlet for conforming mortgage loans to their member institutions. Depending on the district, each FHLB's program is referred to either as the Mortgage Purchase Program (MPP) or Mortgage Partnership Finance (MPF).[2] An important difference between MPP and MPF versus Fannie Mae and Freddie Mac is that the FHLBs do not assume the credit risk associated with the mortgages they purchase. Instead, the FHLBs collect credit enhancements from mortgage originators throughout the life of the loans that they purchase in order to cover potential credit losses; in contrast to the non-refundable g-fees charged on agency loans, in the absence

[2]These two programs differ in regards to some of the products offered and their operational structure, but their distinctions are not relevant to my analysis.

of credit losses, these credit enhancements are returned to the mortgage originator. In this way, mortgage lenders remain responsible for the credit risk of the mortgages they sell to the FHLBs through MPP and MPF but also stand to earn additional income on performing loans.

In Figure 2, I plot the annual mortgage volumes purchased by the FHLBs through MPP and MPF from 2009-2023. In most years, purchase volumes range from $5 billion to $20 billion, reaching a maximum of roughly $22 billion in 2019. In Figure 3, I plot the concentration of these purchases on the continental US, where darker counties correspond to counties in which the FHLBs have purchased a greater overall share of mortgages. MPP and MPF purchases tend to be most heavily concentrated in the districts of Cincinnati, Indianapolis, Chicago, Des Moines, and Topeka.

Figure 2: Annual MPP & MPF Purchase Volumes

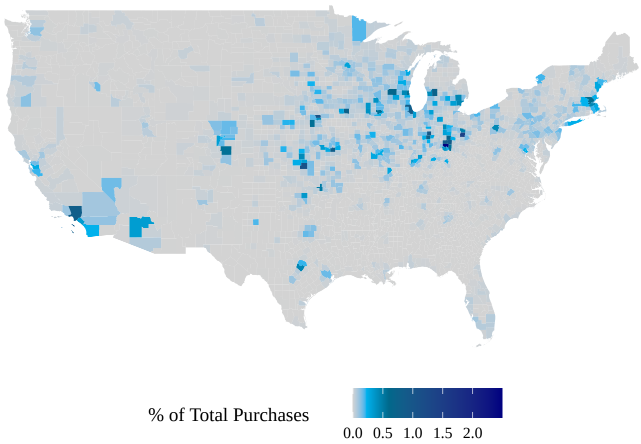


Note: This figure reports annual MPP and MPF purchase volumes from 2009-2023.

There are several possible explanations for the clustering of FHLB mortgage purchases in Midwestern districts observed in Figure 3. First, FHLBs in the Midwestern districts typically have the highest levels of membership and thus the largest balance sheets.[3] This may lead to both higher demand and supply for FHLB mortgage credit, with more members leading to wider use of the programs and larger balance sheets allowing FHLBs

[3]Differences in FHLB district membership are geographically determined and result from the distribution of regional financial institution headquarters throughout the US.

Figure 3: Concentration of MPP & MPF Purchases



Note: This figure plots the concentration of MPP and MPF purchases on the continental US from 2009-2023. The scale is calculated as the number of mortgages purchased by the FHLBs in a given county divided by the total number of mortgages purchased by the FHLBs, multiplied by 100 to be expressed as a percentage.

to purchase and retain more mortgages from their members. To investigate this hypothesis, in Table 1, for the years 2010-2023, I regress FHLB membership counts for different types of financial institutions by district on the number of mortgages purchased by the corresponding FHLB. I exclude district fixed effects to understand how these factors drive FHLB mortgage purchases in the cross section. I find that districts with larger numbers of commercial bank members have more active FHLB mortgage programs at a statistically significant level but that this relationship does not hold for credit unions and thrift institutions. Thus, it seems likely that at least some of the disparity in FHLB mortgage purchase volumes between districts are driven by differences in commercial bank membership levels, whether this be through the demand or supply channels described above or some combination thereof.

Given the R^2 of only 0.138 in Table 1, it seems that there are other factors that contribute to the disparity in FHLB mortgage purchase volumes between districts. Another such contributing factor may be home prices. In Table 5, I document that lenders with a larger share of small-dollar mortgages ex ante are more likely to adopt MPP and MPF. Thus, it is possible that MPP and MPF experience higher demand in Midwestern districts

Table 1: Impact of Membership Counts on FHLB Mortgage Purchase Volumes by District

	(1)
log(Commercial Bank Membership)	0.441**
	(0.199)
log(Credit Union Membership)	0.066
	(0.231)
log(Thrift Institution Membership)	−0.087
	(0.174)
Observations	132
Fixed Effects	Year
RMSE	0.946
Adjusted R^2	0.138
Within R^2	0.118

Note: This table presents OLS regression estimates examining the relationship between membership counts by financial institution types and total FHLB mortgage purchases by district. The membership counts are calculated through the HMDA Lender file constructed by Robert Avery and maintained by Neil Bhutta at https://sites.google.com/site/neilbhutta/data?authuser=0. The dependent variable is the logarithm of total purchases made by each FHLB in the years 2010-2023. The model includes year fixed effects with standard errors clustered at the year level. Significance levels are denoted as follows: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

among lenders originating smaller mortgages who may find any additional savings earned through these programs worthwhile, while lenders in coastal districts who originate much larger mortgages may not find the incremental savings attractive enough to incentivize participation in the program. Similarly, on the supply side, FHLBs in coastal districts may not be as willing to accept the increased losses associated with interest rate risk on larger mortgages as well as to accept the increased exposure to natural disaster risks in coastal areas. A final potential explanation may be ability to offer attractive pricing to members. Because each FHLB determines the price they offer members for their mortgages, some FHLBS may be less able to or simply choose not to offer as competitive of prices as other FHLBs. Unfortunately, these factors are difficult to test, but they all may factor into the concentration of purchases in Figure 3 in the Midwestern FHLB districts.

4 Conceptual Framework

In this section, I present a simple model that serves as a roadmap for my empirical tests, highlighting the main predictions of the model.

4.1 Model Framework

This model examines how lenders make mortgage origination and secondary market decisions when they have the choice to either retain loans on their balance sheets (R) or sell loans on the secondary market.

Initially, lenders have access to two options: retain loans on their balance sheets or sell them to Fannie Mae and Freddie Mac (S_{GSE}). Lenders earn interest rate r_L on retained loans but bear market risk m and credit risk λp, where $p \in (0, 1)$ is the probability of default which varies across loans according to a probability distribution function $f(p)$ and $\lambda \in [0, 1]$ is the expected loss given default which is positively correlated with p to reflect higher expected losses on riskier mortgage originations (Ganong and Noel (2023)). Additionally, lenders face a cost of funds $c(R)$ on retained loans which is increasing in volume ($c'(R) > 0$). When selling loans to Fannie Mae and Freddie Mac, lenders receive a price P_{GSE} and transfer both market and credit risk, but they incur a guarantee fee $\phi(p)$ which increases with the loan's credit risk ($\phi'(p) > 0$).

Thus, I assume that lenders originate and retain or securitize loans in order to optimize profits according to:

$$\Pi = \underbrace{r_L R - \lambda \mathbb{E}[p] R - mR - c(R)}_{\text{Net Profits on Retained Loans}} + \underbrace{\int_0^1 (P_{GSE} - \phi(p)) S_{GSE} f(p) dp}_{\text{Net Profits from GSE Securitization}}$$

subject to capacity constraints $S_{GSE} \leq \bar{S}_{GSE}$ to reflect the fact that Fannie Mae and Freddie Mac do not have unlimited capacity to absorb mortgages.

Additionally, FHLB system members have the option to join MPP and MPF, providing them with a third option upon mortgage origination. I denote loans sold to the FHLBs by S_{FHLB}. Lenders receive a price P_{FHLB} and transfer market risk, but they retain credit risk λp on these mortgages. Thus, lenders who opt into MPP and MPP earn profits given by

$$\Pi = \underbrace{r_L R - \lambda \mathbb{E}[p] R - mR - c(R)}_{\text{Net Profits on Retained Loans}} + \underbrace{\int_0^1 (P_{GSE} - \phi(p)) S_{GSE} f(p) dp}_{\text{Net Profits from GSE Securitization}}$$

$$+\underbrace{\int_0^1 (P_{FHLB} - \lambda p) S_{FHLB} f(p) dp}_{\text{Net Profits from FHLB Sales}}$$

where again $S_{FHLB} \leq \bar{S}_{FHLB}$ to reflect the fact that the FHLBs do not have unlimited capacity to absorb mortgages.

4.2 Model Predictions

Prediction 1: Participation in the FHLB programs will be particularly high among lenders who have limited funding capacity and lenders who find Fannie Mae and Freddie Mac fees most costly.

Intuition: Lenders choose to participate in MPP and MPF either because FHLB mortgage credit is a cheaper alternative than current sources or expected profits on new originations through the program are positive. In the former case, we must have that lenders prefer FHLB credit over balance sheet credit, meaning $P_{FHLB} - \lambda p > r_L - \lambda p - m - c(R)$, or lenders prefer FHLB credit over GSE credit, meaning $P_{FHLB} - \lambda p > P_{GSE} - \phi(p)$.

Lenders who experience limited funding capacity $c(R)$ would be more likely to prefer FHLB credit over balance sheet credit. These may be lenders who originate a high volume of mortgages relative to their total balance sheet capacity, such as thrift, or savings and loan (S&L), institutions which primarily specialize in originating mortgages to residential consumers. Lenders who find losses on guarantee fees to be particularly costly or who are most interested in pursuing marginal profits on loan originations would be more likely to prefer FHLB credit over GSE credit, assuming that at least part of the attractiveness of the FHLBs as a source of credit are competitive prices P_{FHLB}. These may include small dollar mortgage lenders who suffer from relatively large upfront costs relative to their anticipated income on loan originations, meaning they may have particularly high returns on marginal increases in profits offered by the FHLBs.

Meanwhile, the observation that lenders who expect positive profits on new originations through the FHLBs will also join these programs leads to the next prediction.

Prediction 2: Participation in the FHLB programs may increase mortgage lending but only for low- and medium-risk borrowers. Small dollar lending may also increase.

Intuition: Lenders adopt the FHLB programs to expand mortgage originations only if expected profits are greater than 0, or $P_{FHLB} > \lambda p$. Since λ and p are higher for riskier borrowers, lenders should expand originations primarily for low- and medium-risk borrowers. Moreover, because profitability and regulatory burden are one of the main barriers to origination for small dollar mortgages (Horowitz and Roche (2023); D'Acunto and Rossi (2022)) rather than simply credit risk, FHLB credit should increase small dollar lending given that $P_{FHLB} > \lambda p$ is more likely to be true for small dollar mortgage application rejections prior to the credit shock provided by the FHLBs.

Prediction 3: Use of FHLB credit may lead to a decrease in GSE securitization volumes. This relationship may be heterogeneous with respect to credit risk, but it is not clear whether this substitution will be stronger for high- or low-risk loans.

Intuition: If lenders have additional low- and medium-risk mortgage applicants for which they can expand mortgage origination volumes such that they maximize their use of FHLB credit (i.e. $S_{FHLB} = \bar{S}_{FHLB}$), then they will likely continue to also securitize the maximum volume of loans with Fannie Mae and Freddie Mac (i.e. $S_{GSE} = \bar{S}_{GSE}$). However, if lenders do not have additional low- and medium-risk mortgage applicants to whom they can lend, use of GSE credit S_{GSE} may decline if lenders find FHLB credit to be more profitable. This will be the case when $P_{FHLB} - \lambda p > P_{GSE} - \phi(p)$.

Because both of these arguments are decreasing in credit risk p, it is not immediately obvious whether lenders will substitute GSE credit with low, medium or high risk loans, if at all. If lenders believe that the steeper guarantee fees on medium- or high-risk loans are too costly relative to the true expected losses, lenders may choose to sell these loans to the FHLBs rather than the GSEs. If lenders prefer to recover the less steep guarantee fees on low-risk loans with high probability while avoiding potential credit losses on medium- and high-risk loans, they may choose to sell low-risk loans to the FHLBs and medium- and high-risk loans to the GSEs.

Prediction 4: Use of FHLB credit should not affect the volume of mortgages that lenders retain on their balance sheets.

Intuition: Under the assumption of profit maximization, lenders retain the volume R

of loans on their balance sheets such that $r_L - \lambda p - m = c'(R)$. Since the introduction of FHLB credit does not affect r_L, λ, p, nor R, the first order condition for retained loans remains the same. Moreover, because r_L includes both principal repayment and associated interest, $P_{FHLB} > r_L - m$ will generally not be true unless FHLB prices do not adequately account for market risk. Thus, $r_L - \lambda p - m > P_{FHLB} - \lambda p$ should hold, meaning lenders should first satisfy their optimal retention volume before utilizing FHLB credit.

5 Data

In this section, I describe the two main data sources that I use to identify MPP and MPF program participation and to then link them to mortgage lending activity and secondary market outcomes.

5.1 FHFA MPP and MPF Loan Data

My first data source is the entire population of MPP and MPF loans purchased by all FHLBs from 2009-2023, which is provided by the Federal Housing Finance Agency (FHFA). Every year since 2009, the FHFA has published a public use database containing data pertaining to all mortgages purchased by each Federal Home Loan Bank.[4] The data contains rich information spanning geography, borrower financial characteristics and demographics, and loan characteristics. The data includes over 800,000 loan records.

5.2 Home Mortgage Disclosure Act (HMDA) Data

My second data source is the Home Mortgage Disclosure Act (HMDA) database, a public database that contains detailed information on the majority of mortgage applications across the United States each year. Since 2007, the Consumer Financial Protection Bureau has maintained an online public database containing application-level information

[4]The data is available underneath the "Public Use Database - Federal Home Loan Bank System (FHLBank)" header at this link: https://www.fhfa.gov/data/pudb. At the time of my writing, the FHFA only has the 2023 FHLB Public Use Database published on their website. When I began this project, datasets for each year from 2009-2023 were available.

on mortgage characteristics (e.g., loan amount, loan purpose, etc.), applicant characteristics (e.g., age, gender, race, ethnicity, etc.), and mortgage application outcomes (e.g., approved or rejected). The dataset covers the majority of mortgage lenders in the US, with millions of records in each year of data. For this project, I relied on the HMDA data corresponding to the years for which I had MPP and MPF data, namely 2009 onward.

6 Methodology

6.1 Sample Construction

In order to identify causal effects of MPP and MPF, I use the FHFA MPP and MPF loan data to construct a sample of FHLB members who adopt the programs and then use the HMDA data to observe mortgage market activity and outcomes at the annual level for each of these institutions. With sufficient pre- and post-adoption year observations, this allows me to causally link changes in mortgage lending directly to take-up and continued participation in MPP and MPF.

Constructing this sample presented three main challenges. First, to link individual lenders to the MPP and MPF programs, I must observe the lender associated with each MPP and MPF loan. From 2009-2014, the FHFA data included the seller institution of each mortgage sold to MPP and MPF, but since 2015, this variable has not been made available. To recover the lender associated with each loan after 2014, I merged the FHFA MPP and MPF data to HMDA which records the lender associated with each mortgage application. In Table 2, I report both the non-unique and unique success rates of this match across several sets of variables for a sample of MPP and MPF loans originated in Ohio in 2023.[5] The non-unique match rate is defined as the percentage of loans in the FHFA data which are matched to an observation in HMDA, including loans that are matched to multiple observations as well as multiple loans that are matched to the same observation. The unique match rate is defined as the perctange of loans in the FHFA data which are uniquely mapped 1-to-1 to an observation in the HMDA data. I find

[5]When performing this match using Loan-to-Value (LTV) ratios, I round LTV to the nearest 10^{th} percent to adjust for inconsistencies in reporting between the FHFA and HMDA data.

that, up to the inclusion of the census tract, note amount, and interest rate variables, the non-unique and unique match rates converge to within 1-2% of each other and that the maximal unique match rate is relatively insensitive to the addition of further matching variables. While the match rate varies significantly between sample years, this pattern generally holds regardless of the sample of loans chosen.

Table 2: FHLB & HMDA Sample Match Rates

Match Variables	Unique Match Rate	Non-Unique Match Rate
Census Tract & Note Amount	22.5%	94.0%
Census Tract, Note Amount, & Interest Rate	67.8%	74.6%
Census Tract, Note Amount, Interest Rate, & Loan Purpose	67.3%	72.2%
Census Tract, Note Amount, Interest Rate, Loan Purpose, & Loan-to-Value	68.5%	69.6%
Census Tract, Note Amount, Interest Rate, Loan Purpose, Loan-to-Value, & Loan Term	68.3%	69.5%
Census Tract, Note Amount, Interest Rate, Loan Purpose, Loan-to-Value, Loan Term, & Number of Units	68.4%	69.5%

Note: This table reports the unique and non-unique match rates between FHFA MPP and MPF data and HMDA data for different sets of variables. The non-unique match rate is defined as the percentage of loans in the FHFA data which are matched to an observation in HMDA, including loans that are matched to multiple observations as well as multiple loans that are matched to the same observation. The unique match rate is defined as the perctange of loans in the FHFA data which are uniquely mapped 1-to-1 to an observation in the HMDA data. Match rates in this table are reported for the population of MPP and MPF loans originated in the state of Ohio in 2023. While the match rates are generally variable between years, the pattern and rank of the variables in this table in terms of maximal unique match rate was consistent across different samples.

I ultimately match the FHFA data to HMDA for the years 2018-2023 using the full set of variables which includes census tract, loan size, interest rate, loan purpose, loan-to-value ratio, loan term, and number of units on the property. Because the HMDA data did not include the interest rate nor loan-to-value (LTV) ratio variables prior to 2018, I perform the match for the years 2015-2017 along the same set of variables except for these two. I report the unique match rates associated with each year of this merge in Table 3. The match rates vary significantly across years, with minimal and maximal unique match rates of 27.9% and 70.6% in the years 2016 and 2023, respectively. In particular, the match rate falls in 2020 and 2021 when interest rates were very low and mortgage origination volumes were very high. This could be due to an increase in non-unique matches in these years given the increased mortgage application pool or to under-reporting in these years as mortgage lenders struggled to keep pace with a surge in mortgage applications. Moreover, the match rates in the years 2015-2017 are significantly lower due to the missing interest rate and LTV variables, leading to more non-unique matches.

Table 3: FHLB & HMDA Dataset Match Rates

Year	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
Match %	29.7%	27.9%	42.9%	43.6%	57.7%	39.6%	40.0%	59.1%	70.6%

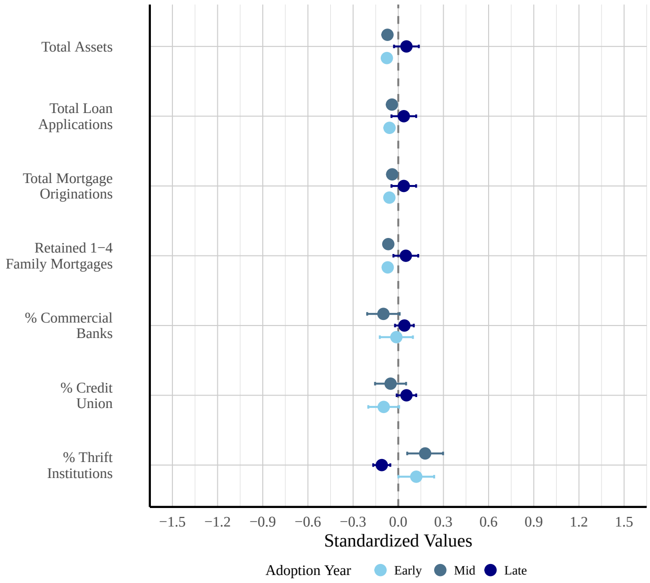
Note: This table reports the match rates associated with the merger of the FHFA and HMDA datasets. For 2018-2023, I match along the following set of variables, dropping all non-unique matches: census tract, loan size, interest rate, loan purpose, loan-to-value ratio, loan term, and number of units on the property. For 2015-2017, the matching set of variables does not include interest rate nor LTV due to their absence in the data in these years.

Because there are a significant number of MPP and MPF loans for which I do not recover a lender, I restrict my sample to a balanced panel, keeping only lenders who appear both in 2009-2014 and 2015-2023. In this way, I avoid making inferences on lenders who first adopt the program after 2014, for whom I may or may not be observing the true program adoption year. Thus, all lenders in my sample adopt the MPP or MPF program prior to 2015.

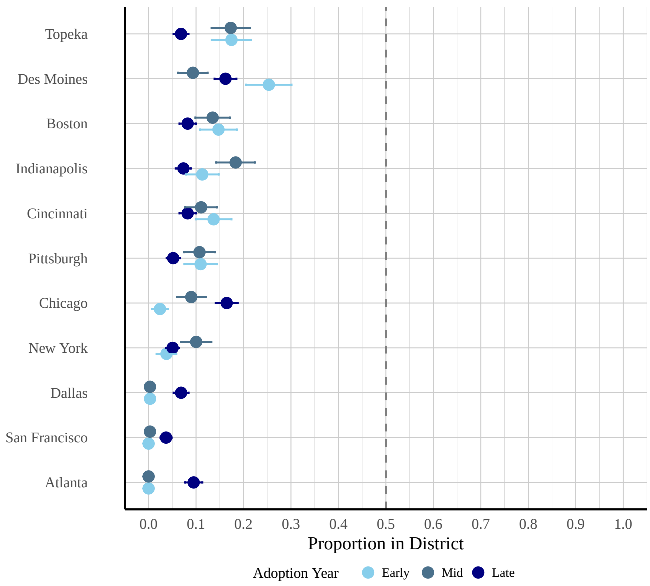
The second challenge I face in constructing my sample stems from the fact that the FHFA MPP and MPF data does not go back to the inception of the programs in the early 2000s when many early users adopted the program. Because the data begins in 2009, I observe over 300 lenders who have already adopted the program in the first year in which I observe data. Since I cannot identify an exact adoption year for these lenders nor can I properly identify pre-trends in their mortgage lending activity prior to program adoption, I remove them entirely from my sample. Thus, my sample is ultimately restricted to lenders who adopt MPP or MPF in the years 2010-2014.

Figure 4: Balance Test: Early, Mid, and Late Cohorts of MPP and MPF Adopters, 2009-2023

(A) Institution-Level Balance Test



(B) District-Level Balance Test



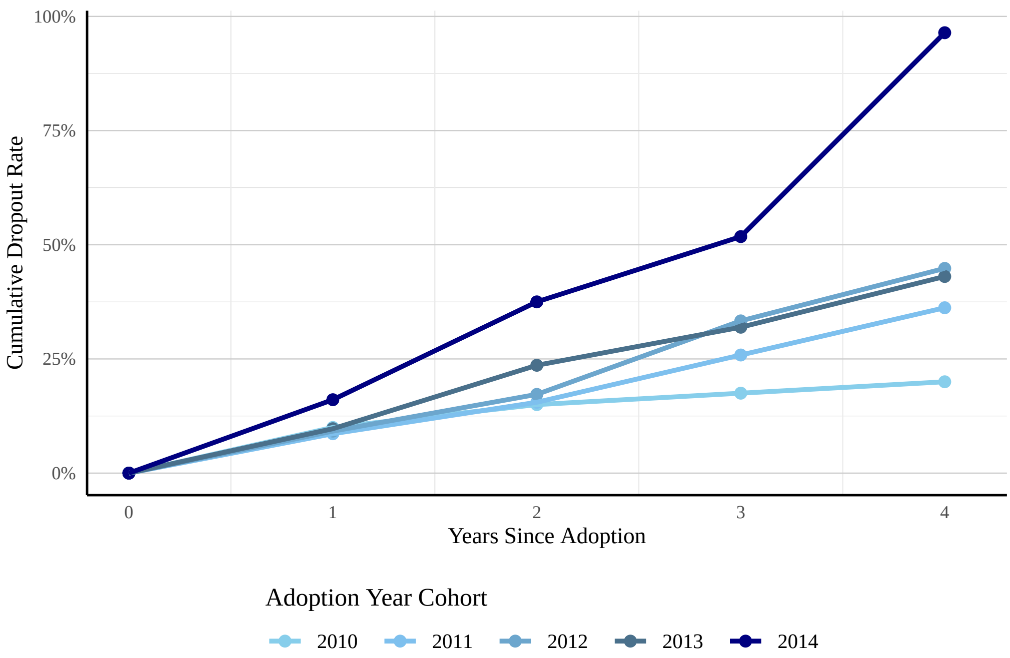
Note: These graphs compare characteristics for mortgage lenders who adopt MPP or MPF pre-2010 (early), 2010-2014 (mid), and 2015-2023 (late). The sizes of the early, mid, and late groups are $n = 330$, 339, and 978, respectively. In order to compare lenders across consistent information, I use variables as of 2009 for all lenders, the first year for which I have data. Panel A compares mean institution-level variables as well as the proportion of institutions that are commercial banks, credit unions, and thrift institutions within each cohort. Panel B compares the proportion of institutions within each cohort which are members of each FHLB district. Note that FHLB Dallas, San Francisco, and Atlanta were not participating in mortgage finance programs in 2009-2014, so all lenders in these districts appear iny my data only in the late adoption cohort. Variables are calculated using the HMDA Lender File constructed by Robert Avery and maintained by Neil Bhutta at https://sites.google.com/site/neilbhutta/data?authuser=0. Bars indicate 95% confidence intervals for the sample means.

In Figure 4, I compare the composition of lenders who adopt MPP and MPF before, during, and after my sample window both at the institution level and FHLB district level to understand the representativeness of my sample. There are 1,637 lenders in total, with roughly 300 in each of the early and mid adoption groups and roughly 1,000 in the late adoption group. To account for the wide range of adoption years in my sample, I compare all variables across lenders as of 2009, the earliest year in my data. In Panel A, I find that lenders in the early, mid, and late adoption cohorts are similar across balance sheet size and mortgage market volume variables, and the composition of lenders among commercial banks, credit unions, and thrift institutions is fairly constant across all three groups as well. Moreover, in Panel B, I find that the distribution of each cohort across FHLB districts is fairly stable, although no lenders in FHLB Dallas, San Francisco, and Atlanta appear in the early and mid adoption cohorts as these FHLBs were not participating in mortgage finance programs in 2009-2014. These results provide evidence to suggest that despite a narrow sample window, my findings may be generalizable to adopters of MPP and MPF in earlier and later years.

The final challenge I face in constructing my sample results from the fact that some lenders who adopt MPP and MPF subsequently discontinue their use of the program only a few years later. Thus, I cannot observe full post-adoption effects of participation in MPP and MPF due to dropout from treatment, which in this case is endogenous to the lender. To account for this issue, I remove all lenders from my sample who do not participate in MPP or MPF for at least four continuous years following program adoption, thereby allowing me to assume that program take-up in my sample is binding but reducing the generalizability of my findings to lenders who find MPP and MPF beneficial enough to continue their participation for several years.

In Figure 5, I examine the impacts of removing lenders who drop MPP and MPF before four years of continuous use from my sample by plotting observed MPP and MPF dropout rates by adoption year cohort. I find that dropout rates for the 2010 and 2011 adoption cohort are relatively low, with roughly 75% of lenders still using MPP and MPF after four years of program use for both cohorts. However, cumulative dropout seems to

Figure 5: MPP and MPF Dropout Rates by Adoption Year Cohort



Note: This figure plots MPP and MPF dropout rates by adoption year cohorts 2010-2014. Notice that dropout rates significantly increase for later adoption year cohorts due to poor lender coverage in the merged HMDA and FHFA data for 2015-2017, leading to unrealistically high dropout among lenders in these years.

increase significantly with each subsequent cohort. This phenomenon almost certainly stems from the low match rates between HMDA and the FHFA data in the years 2015-2017 in which I attempted to recover the lender associated with each MPP and MPF loan reported in Table 3. Thus, the higher observed dropout rates for later adoption year cohorts are likely driven more by undercoverage in my sample rather than by actual dropout. This means that by removing instances of dropout, I am removing many lenders from the later adoption cohorts in my sample who likely did indeed stick with treatment for the full post-adoption period.

Ultimately, my sample is constructed to include lenders who adopt MPP or MPF in the years 2010-2014 and who appear in my sample for four consecutive years, with undercoverage leading to lower totals in later adoption year cohorts than would otherwise be true. In Table 4, I report the number of lenders in each adoption year cohort of my sample.

Table 4: MPP & MPF Program Adoptions by Year

Year	2010	2011	2012	2013	2014
Total Adoptions	33	44	58	49	29

Note: This table reports the number of lenders in each MPP and MPF adoption year cohort in my final sample.

6.2 Identification Strategy

To study the effects of MPP and MPF on participating institutions' mortgage lending activity over time, I use the dynamic difference-in-differences design

$$Y_{i,t} = \sum_{t=-2, t\neq -1}^{t=2} \beta_t Adoption_{i,t} + \gamma' \mathbf{X}_{i,t} + \eta_i + \theta_t + \epsilon_{i,t} \tag{6.1}$$

where i indexes lending institutions and t indexes years. I include two-way fixed effects, with η_i denoting lender fixed effects and θ_t denoting year fixed effects. Here, $Y_{i,t}$ is a mortgage lending outcome variable of interest, $Adoption_{i,t}$ is a factor variable equal to the number of years relative to MPP or MPF adoption for lender i in year t, equal to 0 if lender i adopts the MPP or MPF program in year t. I estimate coefficients β_t for the two years prior to program adoption to explore pre-trends in the outcome variable prior to MPP or MPF adoption and for the three years following program adoption to understand how the effects of the MPP and MPF programs vary over time. Following Roth (2024), I estimate all specifications of (6.1) in long-differences for the pre-treatment and post-treatment coefficients so that pre-trends on the β_t coefficients are visually interpretable relative to the reference period $t = -1$. Finally, $\mathbf{X}_{i,t}$ is a set of lender controls that is specific to each regression specification.

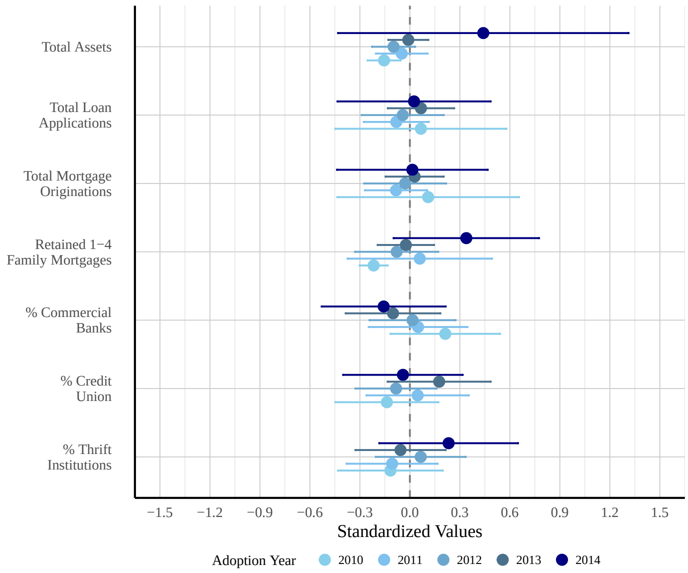
Because the adoption year across lenders in my sample is not constant, I estimate (6.1) with variation in treatment timing. Thus, in each specification of 6.1, I report two sets of results. First, I report the standard OLS estimates which may be biased in this setting. Second, I report results obtained from using the estimator proposed in Callaway and Sant'Anna (2021), which is specifically designed to produce an unbiased estimate of (6.1) accounting for possible heterogeneity in treatment timing. Any differences between the two estimates likely implies treatment effect heterogeneity among MPP and MPF adoption year cohorts.

Finally, because institutional demand as well as access to the MPP and MPF programs may be endogenous to lending market outcomes, comparing lenders who adopt the MPP or MPF program to lenders who do not adopt the program will likely lead to biased estimates. For instance, most users of the MPP and MPF programs tend to be small, local or regional lenders, so using the lending activity of large, national mortgage companies such as Rocket Mortgage as a baseline against which to compare the changes in lending activity brought about by the MPP and MPF programs is not a balanced comparison. Thus, in all specifications of (6.1), I use the not-yet-treated lenders, or the lenders who will but have not yet adopted the MPP and MPF programs, as the control group. Thus, I compare early MPP and MPF adopters to late MPP and MPF adopters, which helps to minimize the selection bias associated with my estimates. The identifying assumption in this research design is that in the absence of MPP and MPF program adoption, mortgage lending outcomes for early within-sample adopters would have evolved similarly to lending outcomes of late within-sample adopters.

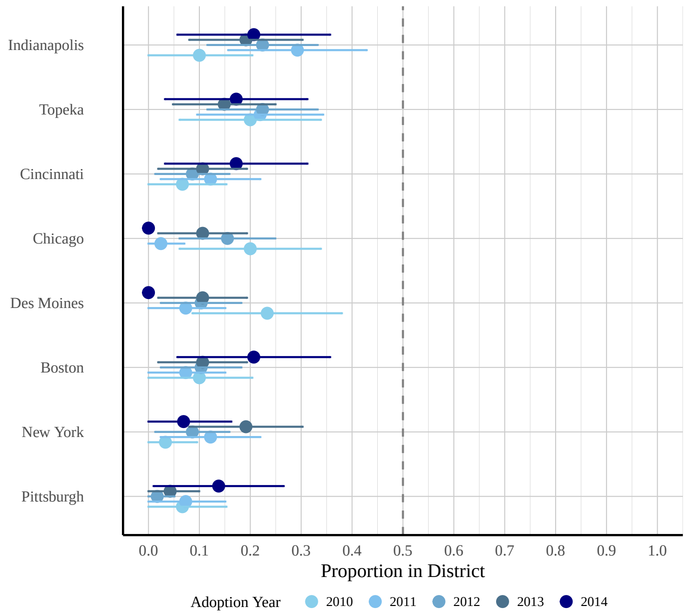
Figure 6 supports the notion that comparing early versus later cohorts of program adopters helps hold fixed selection on observables which contribute to MPP and MPF adoption. Panel A shows that different adoption year cohorts have similar levels of total assets, mortgage application and origination volumes, and mortgages retained on balance sheets, and the relative composition of each adoption year cohort is comprised of similar proportions of commercial banks, credit unions, and thrift institutions each year. The only exception to this is the 2014 cohort which has larger average total assets than any other cohort; this is partially due to this cohort having the smallest sample size and containing one lender who was much larger than any other institution who adopted MPP or MPF in my sample. Moreover, Panel B shows that the district composition of each adoption cohort remains relatively stable, meaning the number of adopters in each cohort each year does not vary significantly.

Figure 6: Balance Test: Comparing Within-Sample Early vs. Late Cohorts of MPP and MPF Adopters, 2010-2014

(A) Institution-Level Balance Test



(B) District-Level Balance Test



Note: These plots compare characteristics for mortgage lenders who adopt MPP or MPF in different years within my sample, 2010-2014. To conduct this comparison, I use variables as of the year prior to program adoption for each cohort. Panel A compares mean institution-level variables as well as the proportion of institutions that are commercial banks, credit unions, and thrift institutions within each cohort. Panel B compares the proportion of institutions within each cohort which are members of each FHLB district. Note that the San Francisco, Atlanta, and Dallas districts do not appear in my sample as these FHLBs were not participating in mortgage finance programs in these years. Variables are calculated using the HMDA Lender File constructed by Robert Avery and maintained by Neil Bhutta at https://sites.google.com/site/neilbhutta/data?authuser=0. Bars indicate 95% confidence intervals for the sample means.

6.3 Descriptive Statistics on MPP and MPF Adoption

I investigate which factors predict MPP and MPF adoption at the institution level in Table 5. I run linear probability models of the form

$$Adopted_{i,t} = \gamma' \mathbf{X}_{i,t} + \eta_i + \theta_t + \epsilon_{i,t} \tag{6.2}$$

where my control group is mortgage lenders in the FHLB system who never adopt MPP or MPF. In column (1), I explore which factors predict whether a mortgage lender will eventually adopt MPP or MPF at any point in my sample. Thus, $Adopted_{i,t}$ is set to one if lender i adopts MPP or MPF in any year after year t, where I exclude all observations of lenders who adopt MPP or MPF in or before time t to avoid potential confounding. I do not control for lender fixed effects as I am interested in differences *between* lenders that help to predict MPP and MPF adoption. In column (2), I explore which factors predict the *timing* of adoption of MPP or MPF for each lender who adopts the program. I set $Adopted_{i,t}$ to one if lender i adopts MPP or MPF in year $t+1$, thus predicting program adoption on a one year lag in order understand how trends in mortgage lending prior to adoption predict program take-up, again excluding all observations of lenders who adopt MPP or MPF in or before time t to avoid potential confounding. I include lender fixed effects in order to focus on changes *within* lenders that predict program adoption.

In column (1), I find that lenders who originate a larger share of refinance and home purchase loans (relative to home improvement loans) are more likely to adopt MPP and MPF. I find that, strictly among FHLB system mortgage lenders, lenders who originate more mortgages are more likely to adopt the programs. I also find that lenders who serve a higher share of low-income borrowers relative to local census tract median incomes and lenders who originate a larger share of small-dollar mortgages are more likely to adopt the program. As explained in Prediction 1 of Section 4, this may be due to increased profitability on loans sold through MPP and MPF, whether that be through cheaper pricing, the absence of guarantee fees, or some combination thereof, which may be more

Table 5: Determinants of MPP and MPF Adoption

	(1)	(2)
Mortgage Approval Rates	0.017	-0.004
	(0.010)	(0.006)
% Loan Applications from Women	0.077	-0.032^{***}
	(0.053)	(0.007)
% Refinance Applications	0.040^{**}	0.010
	(0.016)	(0.007)
% For Purchase Applications	0.067^{*}	-0.019^{***}
	(0.032)	(0.006)
Fannie Freddie Securitizations	0.000	-0.000
	(0.000)	(0.000)
log(Mortgage Origination Volume)	0.032^{**}	-0.001
	(0.011)	(0.001)
Mortgages Retained	0.000	-0.000
	(0.000)	(0.000)
% Small Dollar Mortgages	0.056^{**}	0.009
	(0.020)	(0.006)
Percent Minority Loans	-0.117^{**}	-0.001
	(0.047)	(0.007)
Average Income to Census Tract Median Family Income Ratio	-0.001^{**}	0.000
	(0.001)	(0.000)
log(Total Assets)	-0.008	-0.008^{**}
	(0.005)	(0.003)
Thrift Institution	0.037^{**}	
	(0.013)	
Credit Union	0.004	
	(0.007)	
Observations	28,238	28,238
Adj. R^2	0.113	0.080
Year FE	Yes	Yes
Lender FE	No	Yes

Note: This table examines predictors of mortgage lenders' adoption of MPP and MPF. The dependent variable $Adopted_{i,t}$ is an indicator variable denoting adoption of MPP or MPF. In column (1), I explore factors that predict adoption of MPP and MPF *between* lenders. Thus, I exclude lender fixed effects and set $Adopted_{i,t}$ equal to one if lender i adopts MPP or MPF in any year after year t, excluding all observations of lenders who adopt MPP or MPF in or before time t to avoid potential confounding. In column (2), I explore factors that predict the timing of adoption of MPP and MPF *within* individual lenders. Thus, I include lender fixed effects and set $Adopted_{i,t}$ equal to one if lender i adopts MPP or MPF in year $t+1$, again excluding all observations of lenders who adopt MPP or MPF in or before time t to avoid potential confounding. All predictors are calculated via HMDA or the HMDA lender file. Standard errors are clustered at the year level in (1) and at the lender level in (2) and are reported in parentheses. Significance levels are denoted as follows: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

important to lenders who serve lower income borrowers with smaller loan amounts as these lenders may experience lower profitability ex ante (Horowitz and Roche (2023); Amornsiripanitch and Ricks (2024)). Interestingly, I find that mortgage lenders who serve more minority populations are less likely to adopt MPP and MPF. This may be due to the geographic concentration of MPP and MPF loans in the Midwest, which tends to be less diverse than other regions of the country. Finally, I find that thrift institutions, which are institutions which specialize in originating home mortgages for consumers, are more likely to adopt MPP and MPF than credit unions and commercial banks, the reference institution category in this regression. This may be due to the fact that a larger portion of thrift institutions' business is concentrated in mortgage lending than commercial banks and credit unions, meaning they may have more to gain from additional mortgage credit due to tigher balance sheet capacity constraints.

In column (2), I find that the only statistically significant predictors of the timing of program adoption are a decrease in the percentage of loans written to women, a decrease in the percentage of for-purchase loans, and a decrease in total assets. Decreases in total assets may predict program adoption due to potentially more binding credit constraints, leading lenders to look to the FHLB for additional mortgage credit. However, it is not immediately clear why these demographic factors are predictors of MPP and MPF adoption. Nevertheless, none of these variables seem likely to have an outsized influence on mortgage lending outcomes. Neither changes in volume of mortgage originations nor changes in Fannie Mae and Freddie Mac securitization volumes have significant predictive power with respect to the timing of MPP and MPF adoption. Thus, these results support my identifying assumption in (6.1) that the timing of adoption of MPP and MPF within each institution is quasi-random.

7 Empirical Results

In this section, I present my main empirical findings. I analyze how participation in the FHLB MPP & MPF programs affects equilibrium mortgage lending volumes at the institution level both in aggregate and for small-dollar mortgages. I also explore whether these changes are heterogeneous with respect to loan-to-income (LTI) ratios as a proxy for credit risk. I next estimate the impact of MPP & MPF participation on mortgage application outcomes at the loan level and on mortgage application volumes at the institution level to understand whether equilibrium changes in lending are driven by increases in mortgage supply, demand, or some combination thereof. Finally, I explore how participation in MPP & MPF affects lenders' securitization decisions and whether these effects are heterogeneous with respect to credit risk.

7.1 Impacts of MPP and MPF Participation on Mortgage Origination Volumes

In this section, I analyze how participation in MPP and MPF affect mortgage lenders' equilibrium origination volumes, both in aggregate and in the small-dollar segment. In Section (4), I explained in Prediction 2 that MPP and MPF should increase both total and small-dollar mortgage origination volumes for participating lenders. In Table 6, I explore this prediction by estimating (6.1) with mortgage origination volumes as the outcome variable. Across both the OLS and Callaway and Sant'Anna (2021) specifications, all post-treatment coefficients are positive and generally statistically significant for both total mortgage origination volumes and small-dollar mortgage origination volumes, suggesting both increase by as much as 40% by lenders' third year of using the program. The Callaway and Sant'Anna (2021) estimator produces an average ATT estimate of about 33% for both outcomes, suggesting lenders increase their overall and small-dollar lending by a factor of one third on average following adoption of MPP and MPF. Moreover, the table suggests that there are no significant pre-trends in either outcome variable, supporting the interpretation of these increases as causal.

I now turn to whether MPP and MPF have a differential impact on mortgage origination volumes for borrowers of differing creditworthiness. In Prediction 2 in Section (4), I also explained that MPP and MPF should lead to increased mortgage origination volumes primarily for borrowers of good credit quality since these programs leave lenders

Table 6: Impact of MPP/MPF Participation on Mortgage Origination Volumes

	log(Total Originations)			log(Small-Dollar Originations)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Year -2	-0.016	-0.056		-0.020	-0.114	
	(0.152)	(0.096)		(0.129)	(0.085)	
Treatment Year 0	0.177	0.223^{**}		0.144	0.194	
	(0.161)	(0.092)		(0.154)	(0.095)	
Treatment Year 1	0.265^{*}	0.442^{**}		0.230	0.444^{***}	
	(0.160)	(0.165)		(0.154)	(0.135)	
Treatment Year 2	0.378^{**}	0.347^{*}		0.323^{**}	0.360	
	(0.162)	(0.218)		(0.157)	(0.196)	
Treatment$_{i,t}$			0.337^{***}			0.332^{***}
			(0.130)			(0.123)
Observations	1,072	1,072	1,072	1,070	1,070	1,070
Demographic/Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	CSDID	CSDID	OLS	CSDID	CSDID
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the treatment effects on the treated (ATT) regression coefficient estimates according to (6.1) for both total mortgage lending volumes (columns 1-3) and small-dollar mortgage lending volumes (columns 4-6) as the outcome. Columns (1) and (4) use OLS as the estimator, while columns (2) and (5) use Callaway and Sant'Anna (2021)'s estimator. Columns (3) and (6) report the average treatment effect on the treated (ATT) as calculated by the Callaway and Sant'Anna (2021) estimator. All columns compare early to late MPP and MPF adopters by using the not-yet-treated units as the control group. Following Roth (2024), in the columns using the Callaway and Sant'Anna (2021) estimator, I estimate coefficients for the pre-treatment and post-treatment coefficients in long-differences so that pre-trends on the β_t coefficients are visually interpretable relative to the reference period $t = -1$. I do the same in the OLS column for consistency. Robust standard errors clustered at the lender level are reported in parentheses. Significance levels for estimates using the Callaway and Sant'Anna (2021) estimator are obtained through wild bootstrap with 1,000 replications. Significance levels are denoted as follows: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

responsible for credit risk on mortgages they sell. To test this hypothesis, I stratify all mortgage applications in HMDA based on their loan-to-income (LTI) ratios as a proxy for credit quality, where a higher loan-to-income ratio signals a greater probability of default following a negative income shock (Ganong and Noel (2023)). Specifically, I compare each mortgage application to other applications within the same census tract each year and classify each application as either low, medium, or high LTI. I then estimate (6.1) on each of the three classes of loans separately in Table 7.

I find increases in mortgage origination volumes accrue to low and medium LTI borrowers at statistically and economically significant levels, with mortgage originations to medium LTI borrowers experiencing the largest increases at 50%, according to the av-

Table 7: Heterogeneous Impacts of MPP/MPF Participation on Mortgage Origination Volumes by Credit Risk

	log(Low Risk Originations)			log(Medium Risk Originations)			log(High Risk Originations)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment Year -2	−0.059	−0.107		0.027	−0.010		0.055	0.068	
	(0.141)	(0.086)		(0.191)	(0.130)		(0.153)	(0.143)	
Treatment Year 0	0.117	0.192*		0.199	0.349***		0.134	0.105	
	(0.171)	(0.084)		(0.207)	(0.102)		(0.163)	(0.077)	
Treatment Year 1	0.287*	0.432***		0.288	0.550**		0.172	0.141	
	(0.173)	(0.136)		(0.196)	(0.183)		(0.164)	(0.197)	
Treatment Year 2	0.359*	0.429		0.377*	0.601		0.280*	0.150	
	(0.184)	(0.261)		(0.196)	(0.320)		(0.170)	(0.207)	
$\text{Treatment}_{i,t}$			0.351**			0.500***			0.132
			(0.142)			(0.165)			(0.133)
Observations	1,056	1,056	1,056	1,055	1,055	1,055	1,054	1,054	1,054
Dem./Fin. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	CSDID	CSDID	OLS	CSDID	CSDID	OLS	CSDID	CSDID
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the treatment effects on the treated (ATT) regression coefficient estimates according to (6.1) for total mortgage lending volumes according to loan-to-income (LTI) ratio bands, which are stratified according to terciles calculated within census tracts each year. Columns (1)-(3) correspond to low LTI borrowers (low credit risk), columns (4)-(6) correspond to medium LTI borrowers (medium credit risk), and columns (7)-(9) correspond to high LTI borrowers (high credit risk). Columns (1), (4), and (7) use OLS as the estimator, while columns (2), (5), and (8) use Callaway and Sant'Anna (2021)'s estimator. Columns (3), (6), and (9) report the average treatment effect on the treated (ATT) as calculated by the Callaway and Sant'Anna (2021) estimator. All columns compare early to late MPP and MPF adopters by using the not-yet-treated units as the control group. Following Roth (2024), in the columns using the Callaway and Sant'Anna (2021) estimator, I estimate coefficients for the pre-treatment and post-treatment coefficients in long-differences so that pre-trends on the β_t coefficients are visually interpretable relative to the reference period $t = -1$. I do the same in the OLS column for consistency. Robust standard errors clustered at the lender level are reported in parentheses. Significance levels for estimates using the Callaway and Sant'Anna (2021) estimator are obtained through wild bootstrap with 1,000 replications. Significance levels are denoted as follows: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

erage ATT as calculated by the Callaway and Sant'Anna (2021) estimator. As medium LTI borrowers likely pose relatively little additional risk compared to low LTI borrowers, this result is not surprising given that Table 5 suggests that lenders who adopt MPP and MPF tend to have higher percentages of their portfolios in lower income households which would be more likely to be medium LTI borrowers than low LTI borrowers. Most notably, I find that the increases in mortgage origination volumes that accrue to low and medium LTI borrowers do not appear to accrue to high LTI (or more risky) borrowers. The average ATT as reported by the Callaway and Sant'Anna (2021) estimator for high LTI borrowers is a statistically insignificant 13%, much lower than the 35% and 50%

estimates for low and medium LTI borrowers, respectively, both of which are statistically significant at or beyond the $p = 0.05$ level. This supports the prediction that the through the retention of credit risk on loans sold through MPP and MPF, lenders are only incentivized to increase mortgage origination volumes to creditworthy borrowers. Moreover, I find no statistically significant pre-trends in any of the regressions, providing support for my causal interpretation.

7.2 Impacts of MPP and MPF Participation on Mortgage Approvals

In this section, I analyze how participation in MPP and MPF affect mortgage lenders' application outcomes, again both in aggregate and in the small-dollar segment, in order to understand whether the equilibrium increases in total and small dollar lending documented above are driven by increases in credit supply, demand, or some combination thereof.

There are two possible offsetting effects of MPP and MPF participation on mortgage application outcomes. Because MPP and MPF increase the available amount of secondary market credit, mortgage lenders should have greater capacity for mortgage lending and thus be more likely to approve mortgage applications, all else equal. However, because lenders retain credit risk on mortgage originations sold through MPP and MPF, they are not necessarily incentivized to approve mortgage applications which they otherwise would have denied for reasons related to credit risk, meaning the probability of application approval should not necessarily increase if lenders reject a significant amount of applicants for reasons related to credit risk.

To explore these offsetting effects, I estimate (6.1) both over the population of all mortgage applications and of small-dollar mortgages for all MPP and MPF lenders in my sample, still using the not-yet-treated lenders as my control group. I define my outcome variable $Y_{i,t}$ as 1 if a mortgage application is approved and 0 otherwise. I include borrower and census tract financial and demographic controls such as applicant income, loan amount, borrower income to census tract median income ratio, loan purpose, and census tract minority population to control for observable differences in borrowers that may explain disparities in application outcomes. I report my results in Table 8.

Table 8: Impact of MPP/MPF Participation on Likelihood of Mortgage Application Approvals

	All Mortgages			Small-Dollar Mortgages		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Year -2	-0.059^{**}	-0.019		-0.037	-0.007	
	(0.028)	(0.033)		(0.026)	(0.028)	
Treatment Year 0	-0.123^{**}	-0.007		-0.074	-0.012	
	(0.050)	(0.024)		(0.052)	(0.024)	
Treatment Year 1	0.040^{*}	0.003		0.015	-0.001	
	(0.023)	(0.027)		(0.026)	(0.053)	
Treatment Year 2	0.090^{*}	0.062		0.043	0.025	
	(0.047)	(0.033)		(0.050)	(0.045)	
$\text{Treatment}_{i,t}$			0.019			0.004
			(0.021)			(0.030)
Observations	$996,052$	$996,052$	$996,052$	$358,608$	$358,608$	$358,608$
Demographic/Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	CSDID	CSDID	OLS	CSDID	CSDID
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the treatment effects on the treated (ATT) regression coefficient estimates with the outcome variable being a binary variable set to 1 if a mortgage application is approved and 0 otherwise using OLS in columns (1) and (4) and Callaway and Sant'Anna (2021)'s estimator in columns (2) and (5), comparing early to late MPP and MPF according to (6.1). Columns (3) and (6) report the average treatment effect on the treated (ATT) calculated by the Callaway and Sant'Anna (2021) estimator. Following Roth (2024), in the column using the Callaway and Sant'Anna (2021) estimator, I estimate coefficients for the pre-treatment and post-treatment coefficients in long-differences so that pre-trends on the β_t coefficients are visually interpretable relative to the reference period $t = -1$. I do the same in the OLS column for consistency. Robust standard errors clustered at the lender level are reported in parentheses. Significance levels for estimates using the Callaway and Sant'Anna (2021) estimator are obtained through wild bootstrap with 1,000 replications. Significance levels are denoted as follows: $^{***}: \ p < 0.01$, $^{**}: \ p < 0.05$, $^{*}: p < 0.1$.

Across both OLS and Callaway and Sant'Anna (2021)'s estimator for both all mortgage applications and small-dollar mortgage applications, I find negative coefficients estimates of the effect of treatment on approval probabilities in the first year of treatment but generally positive coefficient estimates for the second and third years of treatment. This suggests that mortgage approval probabilities dip in the first year of treatment but eventually rebound to slightly above their pre-treatment levels. However, these results are generally statistically insignificant and small. Only the OLS estimator on all mortgage applications finds statistically significant results, while all other regressions return no statistically significant estimates. The average ATT on mortgage approval probabilities as reported by the Callaway and Sant'Anna (2021) estimator is only 1.9% for all mortgage applications and 0.4% for small-dollar mortgage applications, both of which are economically and statistically insignificant. Thus, the results in Table 8 generally suggest that MPP and MPF do not have a significant effect on mortgage approval probabilities, controlling for borrower observables.

Table 9: Impact of MPP/MPF Participation on Mortgage Application Volumes

	log(All Mortgage Applications)			log(Small-Dollar Mortgage Applications)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Year -2	-0.026	-0.085		-0.057	-0.151	
	(0.139)	(0.084)		(0.135)	(0.089)	
Treatment Year 0	0.160	0.205*		0.110	0.127	
	(0.149)	(0.085)		(0.155)	(0.093)	
Treatment Year 1	0.251*	0.419***		0.239	0.370***	
	0.143	(0.135)		(0.154)	(0.134)	
Treatment Year 2	0.369**	0.286		0.346**	0.245	
	(0.144)	(0.235)		(0.156)	(0.201)	
$\text{Treatment}_{i,t}$			0.303**			0.248**
			(0.129)			(0.115)
Observations	1,072	1,072	1,072	1,071	1,071	1,071
Demographic/Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	CSDID	CSDID	OLS	CSDID	CSDID
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the treatment effects on the treated (ATT) regression coefficient estimates for mortgage application volumes as the outcome using OLS in columns (1) and (4) and Callaway and Sant'Anna (2021)'s estimator in columns (2) and (5), comparing early to late MPP and MPF according to (6.1). Columns (3) and (6) report the average treatment effect on the treated (ATT) calculated by the Callaway and Sant'Anna (2021) estimator. Following Roth (2024), in the column using the Callaway and Sant'Anna (2021) estimator, I estimate coefficients for the pre-treatment and post-treatment coefficients in long-differences so that pre-trends on the β_t coefficients are visually interpretable relative to the reference period $t = -1$. I do the same in the OLS column for consistency. Robust standard errors clustered at the lender level are reported in parentheses. Significance levels for estimates using the Callaway and Sant'Anna (2021) estimator are obtained through wild bootstrap with 1,000 replications. Significance levels are denoted as follows: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

If approval probabilities not only do not increase significantly but actually decrease slightly immediately following treatment, what drives the increase in mortgage origination volumes for participating MPP and MPF lenders? In Table 9, I explore the impact of MPP and MPF on mortgage application volumes. I find that both total and small-dollar mortgage applications increase at a similar rate to mortgage origination volumes, with average ATT's of 30% and 25%, respectively. Moreoever, I find no evidence of statistically significant pre-trends, providing support for a causal interpretation of these increases. Thus, this suggests that increases in mortgage origination volumes following MPP and MPF participation are driven by increases in overall applications rather than more lenient application screening. This could be due to a variety of factors including lower interest rates, lower application fees, or greater capacity to accept and approve mortgage applications, all of which can plausibly be explained by the additional loan supply made possible by the additional and possibly cheaper mortgage credit offered by MPP and MPF.

7.3 Impacts of MPP and MPF Participation on Securitization Decisions

I now turn to the question of whether participation in MPP and MPF affects lenders' securitization decisions. As I outlined in Section 4 in Predictions 3 and 4, because MPP and MPF provide a potentially cheaper source of mortgage credit than do Fannie Mae and Freddie Mac through the absence of guarantee fees assuming similar pricing, these programs may act as a substitute for Fannie Mae and Freddie Mac. However, the volume of mortgages that lenders retain on their balance sheets is unlikely to decrease unless FHLB prices do not fully account for the market risk associated with holding the loans, an unlikely outcome in a competitive market.

In Table 10, I estimate (6.1) with Fannie Mae and Freddie Mac securitization volumes and volumes of mortgages retained on lenders' balance sheets as the outcome variables. I find evidence that lenders use MPP and MPF credit to substitute Fannie Mae and Freddie Mac credit. While OLS gives non-statistically significant estimates of 25%-30% decreases in the use of agency credit following participation in MPP and MPF, Callaway and Sant'Anna (2021)'s estimator gives much larger statistically significant results, with

Table 10: Impact of MPP/MPF Participation on Lenders' Securitization Decisions

	log(Fannie & Freddie Securitization Volumes)			log(No Securitization Volumes)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Year -2	-0.049	0.018		-0.082	-0.211^{*}	
	(0.326)	(0.116)		(0.139)	(0.084)	
Treatment Year 0	-0.283	-0.386^{**}		0.074	0.078	
	(0.350)	(0.152)		(0.158)	(0.088)	
Treatment Year 1	-0.245	-0.408		0.176	0.248	
	(0.317)	(0.219)		(0.142)	(0.145)	
Treatment Year 2	-0.118	-0.718		0.219	0.038	
	(0.340)	(0.349)		(0.139)	(0.194)	
$\text{Treatment}_{i,t}$			-0.504^{**}			0.121
			(0.200)			(0.113)
Observations	515	515	515	1,065	1,065	1,065
Demographic/Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	CSDID	CSDID	OLS	CSDID	CSDID
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the treatment effects on the treated (ATT) regression coefficient estimates for Fannie Mae and Freddie Mac securitization volumes (columns (1)-(3)) and volumes of mortgages retained on lenders' balance sheets (columns (4)-(6)) as the outcome variables using OLS in columns (1) and (4) and Callaway and Sant'Anna (2021)'s estimator in columns (2) and (5), comparing early to late MPP and MPF according to (6.1). Columns (3) and (6) report the average treatment effect on the treated (ATT) calculated by the Callaway and Sant'Anna (2021) estimator. Following Roth (2024), in the column using the Callaway and Sant'Anna (2021) estimator, I estimate coefficients for the pre-treatment and post-treatment coefficients in long-differences so that pre-trends on the β_t coefficients are visually interpretable relative to the reference period $t = -1$. I do the same in the OLS column for consistency. Robust standard errors clustered at the lender level are reported in parentheses. Significance levels for estimates using the Callaway and Sant'Anna (2021) estimator are obtained through wild bootstrap with 1,000 replications. Significance levels are denoted as follows: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

an estimated average ATT of a 50% reduction in the use of agency credit following participation in MPP and MPF. This provides evidence that lenders have a preference for MPP and MPF credit over agency credit, likely due to more competitive prices, the absence of guarantee fees, or some combination thereof. The absence of statistically significant pre-trends again supports a causal interpretation of these estimates. Meanwhile, I find no evidence that MPP and MPF credit substitutes balance sheet capital used to support mortgages not sold on the secondary market by lenders, with weakly positive increases in the volume of loans that aren't securitized by lenders following participation in MPP and MPF. However, this finding as well as the finding that lenders use MPP and MPF to substitute credit from Fannie Mae and Freddie Mac both provide supporting evidence that increases in mortgage lending following participation in MPP and MPF are the result of MPP and MPF themselves rather than a contemporaneous increase in use of another source of credit.

One interesting question that arises from the finding that lenders substitute agency credit with MPP and MPF credit is whether lenders have a preference for selling loans of higher or lower credit quality through MPP and MPF. In Section 4, I explain in Prediction 3 that there are two plausible ways in which substitution of Fannie Mae and Freddie Mac credit could vary with credit risk. First, since MPP and MPF offer additional income only on performing loans, lenders may choose to substitute Fannie Mae and Freddie Mac securitization for loans of the lowest credit risk with MPP and MPF credit. However, because these loans also face the lowest guarantee fees, lenders may instead choose to replace agency securitization for loans of medium or high credit risk with MPP and MPF credit, particularly if they believe that the probability of these loans defaulting is less than that suggested by agency guarantee fees.

I investigate this question in Table 11, where I estimate (6.1) again with Fannie Mae and Freddie Mac securitization volumes as the outcome variable, this time again partitioning mortgage originations into three credit risk buckets based on loan-to-income (LTI) ratio terciles calculated each year for each census tract. I find that lenders appear to substitute medium and high credit risk agency sales with MPP and MPF credit more than they do low risk agency sales, with the average ATT reported by Callaway and Sant'Anna (2021)'s estimator being more negative and more statistically significant for medium and high risk agency sales than for low risk agency sales. This suggests that lenders prefer to continue to sell low risk loans to Fannie Mae and Freddie Mac given the relatively low g-fees on these loans while instead selling loans that may be associated with steeper g-fees to MPP and MPF, perhaps reflecting lenders' beliefs that g-fees on these loans are too steep relative to their actual risk.

Table 11: Heterogeneous Impact of MPP/MPF Participation on Lenders' Securitization Decisions by Credit Risk

	log(Low Risk Agency Sales)			log(Medium Risk Agency Sales)			log(High Risk Agency Sales)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment Year -2	-0.056	-0.059		-0.245	0.042		-0.089	0.119	
	(0.314)	(0.148)		(0.238)	(0.108)		(0.242)	(0.142)	
Treatment Year 0	-0.288	-0.415^{***}		-0.366	-0.348^{**}		-0.293	-0.229	
	(0.355)	(0.158)		(0.288)	(0.136)		(0.273)	(0.122)	
Treatment Year 1	-0.136	-0.212		-0.253	-0.459		-0.417	-0.329	
	(0.329)	(0.254)		(0.282)	(0.252)		(0.272)	(0.227)	
Treatment Year 2	-0.110	-0.156		-0.122	-1.037		-0.422	-0.616	
	(0.338)	(0.584)		(0.294)	(0.504)		(0.277)	(0.390)	
Treatment$_{i,t}$			-0.261			-0.615^{**}			-0.391^{**}
			(0.274)			(0.246)			(0.201)
Observations	494	494	494	489	489	489	475	475	475
Dem./Fin. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	CSDID	CSDID	OLS	CSDID	CSDID	OLS	CSDID	CSDID
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the treatment effects on the treated (ATT) regression coefficient estimates for Fannie Mae and Freddie Mac securitization volumes stratified by loan-to-income (LTI) ratio as a proxy for credit risk as the outcome variables using OLS in columns (1) and (4) and Callaway and Sant'Anna (2021)'s estimator in columns (2) and (5), comparing early to late MPP and MPF according to (6.1). Columns (3) and (6) report the average treatment effect on the treated (ATT) calculated by the Callaway and Sant'Anna (2021) estimator. Following Roth (2024), in the column using the Callaway and Sant'Anna (2021) estimator, I estimate coefficients for the pre-treatment and post-treatment coefficients in long-differences so that pre-trends on the β_t coefficients are visually interpretable relative to the reference period $t = -1$. I do the same in the OLS column for consistency. Robust standard errors clustered at the lender level are reported in parentheses. Significance levels for estimates using the Callaway and Sant'Anna (2021) estimator are obtained through wild bootstrap with 1,000 replications. Significance levels are denoted as follows: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

8 Conclusion

This paper uses Federal Housing Finance Agency (FHFA) data on mortgages purchased through the FHLB mortgage finance programs as well as Home Mortgage Disclosure Act (HMDA) data to study how the introduction of an additional source of secondary market credit which rewards lenders with additional profits on performing loans affects mortgage lenders' lending and securitization decisions. I present three main results.

First, I find that take-up of the FHLB mortgage finance programs is higher among lenders who serve borrowers with lower incomes relative to other borrowers in their census tract and among lenders who originate more small-dollar mortgages. I also find that participation in the FHLB mortgage finance programs leads to significant increases in both total and small-dollar mortgage lending. This is potentially because low-income and small-dollar mortgages are less profitable ex ante, meaning these lenders benefit most from more competitive pricing, the additional profits earned on loans sold to the FHLBs, or some combination thereof. This finding adds to the literature on small-dollar mortgages by providing support for the hypothesis that one substantial barrier to small-dollar mortgage lending may be low profitability. This finding has important policy implications as it shows that the cost structure of the mortgage market creates a barrier to mortgage access for low-income borrowers and borrowers in financially underserved areas. Through the FHLB mortgage finance programs as a case study, I highlight that decreasing costs associated with the sale of these mortgages on the secondary market may be a potential solution.

Second, I find evidence that the FHLB mortgage finance programs result in significant increases in mortgage lending for primarily lower risk borrowers. This adds to the literature focused on the effects of secondary market credit on risky mortgage lending by highlighting the mechanism by which the FHLBs manage to provide banks with additional secondary market credit without leading to an increase in lending to borrowers with poor credit. Specifically, this mechanism is holding lenders responsible for the credit risk on loans they sell to the program, thereby rewarding lenders with the additional income only for performing loans that would otherwise be lost on guarantee fees.

Third, I show that lenders reveal a preference for FHLB mortgage finance credit over credit offered by Fannie Mae and Freddie Mac. Thus, I show that the FHLBs manage to offer a potentially cheaper form of secondary market credit that does not involve guarantee fees nor any credit risk transfer, adding to the literature studying the effects of securitization costs on mortgage lending decisions. However, the extent to which this preference arises from the lack of guarantee fees versus more competitive pricing is not clear.

There remain several avenues for future research on this topic. Data is a major limitation. With access to data through the FHFA on prices paid by Fannie Mae, Freddie Mac, and the FHLBs for mortgages on the secondary market, one could directly quantify guarantee fee price elasticities using lenders' preference for the FHLB mortgage finance programs in which they do not pay a guarantee fee but retain credit risk on the mortgages they sell. Pricing data would also allow one to better understand the relative roles of pricing and credit risk retention in driving participation in these programs. Moreover, data on mortgage performance for GSE and FHLB loans would provide stronger insights into lenders' sorting of loans by credit risk between Fannie Mae and Freddie Mac versus the FHLB. Finally, access to data on MPP and MPF purchases prior to 2009 as well as richer information on lender participation since 2015 would allow one to examine the generalizability of these findings to early and late adopters of these programs and to better understand how these programs have affected mortgage lending for all FHLB system members since their inception in the early 2000's.

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