Do GSEs Subsidize Mortgage Lending?

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Abstract

A key function of government-sponsored enterprises (GSEs) is insuring mortgage default risk, yet little is known about whether these guarantees are fairly priced. Using a replicating portfolio and prices of reinsured mortgage default risk to value the cash flows from these guarantees, I show GSEs shifted from providing a 20-bps subsidy pre-GFC to earning risk-adjusted profits of 30-bps post-GFC. Following this increase, banks reduce but still securitize a significant fraction of their mortgages through GSEs. At the margin, more balance sheet-constrained lenders rely more heavily on GSE securitization. These results imply that balance sheet constraints limit lenders' ability to substitute away from above-market GSE insurance prices.

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A defining feature of the residential mortgage market in the United States is that it heavily involves government intermediation relative to other credit markets. Government-sponsored enterprises (GSEs) purchase and securitize the majority of mortgages in the economy. If selling to GSEs has been the predominant financing mechanism in the United States over the past 30 years, a crucial question is what makes this government-sponsored arrangement optimal relative to private market-based financing. A key function performed by GSEs is that they transform credit-risky mortgages into credit-risk-free mortgage-backed securities (MBS) by guaranteeing the default risk in exchange for a fee from the lender. These entities are widely believed to subsidize homeownership by charging below-market rates for this insurance. How large are these subsidies, if any? Any mispricing provided by the GSEs is important for understanding the moral hazard lenders face when choosing to retain or securitize their mortgages (Elenev, Landvoigt, and Van Nieuwerburgh, 2016). Further, recent policy discussions around the privatization of Fannie Mae and Freddie Mac underscore the need to articulate what valuable function these intermediaries provide relative to private capital markets and intermediaries.[1] Despite the importance of the GSEs in the mortgage market, however, there is little empirical evidence quantifying the credit risk subsidies of their mortgage guarantees.

In this paper, I begin by taking a cash flow approach to quantify the credit risk subsidy provided by GSEs on their guarantees of residential mortgages. When loan originators securitize their mortgages through GSEs, they offload the mortgages' credit risk in exchange for paying a negotiated guarantee fee to GSEs, who are then required to forward interest and principal to Mortgage-Backed Security (MBS) bondholders in the event of delinquency or default. To measure the subsidy on their pricing of guarantees, I build a new dataset of the cash flows that Freddie Mac receives for writing these guarantee contracts on single-family fixed-rate mortgages originated from 1999 to 2018. I then apply cash flow based risk-adjustment methodologies to estimate the market value an investor would be willing to pay to purchase these cash flows. GSEs provide a credit subsidy if the risk-adjusted present value of these cash flows is negative, i.e., GSEs do not receive large enough premiums to

[1] The Trump administration is currently preparing IPO filings for the GSEs (see https://www.wsj.com/finance/regulation/trump-aiming-to-ipo-fannie-mae-and-freddie-mac-later-this-year-13b138cf?mod=WSJ_WNPOD).

compensate them for insuring the default risk. In contrast, if the cash flows have zero or even a positive NPV, this means that the GSE premiums are fairly priced or that banks pay an above-market rate to sell loans to GSEs, respectively.

To value the guarantees, I apply two cash-flow–based risk-adjustment methodologies: Risk-Adjusted Profit (RAP) (Gupta and Van Nieuwerburgh, 2021; Flanagan, 2025) and Generalized Public Market Equivalent (GPME) (Korteweg and Nagel, 2016). The key idea of RAP is to build a replicating portfolio for the cash flows of nontraded assets using the cash flows of publicly traded securities with observable market prices. When this replicating portfolio spans the relevant priced risks in the cash flows, its market price measures the value of the nontraded asset of interest. To capture the default risk embedded in GSE guarantees, I follow Flanagan (2025) and use benchmarks shown to successfully replicate and price credit-risky debt cash flows when constructing the replicating portfolio. Further, I specifically include mortgage and real estate specific risk factors to capture risks relevant to the guarantees when building the replicating portfolio benchmarks. Similarly, the GPME estimation involves estimating a pricing function that correctly prices publicly traded benchmarks with similar cash flows and using that function to value the GSE guarantees.

Applying these risk-adjustment methodologies to the guarantee cash flows, I find that the present value of Freddie Mac's guarantees on \$5 trillion of fixed-rate, single-family mortgages originated over 1999–2018 is \$0.000–\$0.002 per \$1 of loan guaranteed. This estimate is statistically and economically indistinguishable from zero. This finding indicates that, on average, over the full sample period, Freddie Mac's mortgage guarantees were close to fairly priced rather than subsidized.

Although the overall average is not different from zero, I next document that GSE guarantee valuations differ substantially before and after the Global Financial Crisis (GFC). In the pre-GFC period, Freddie Mac generated a negative, statistically significant risk-adjusted return of –\$0.009 per \$1 of guaranteed loan, implying an annual subsidy of approximately 20 basis points. This subsidy is consistent with the GSEs' implicit government backing and lenders' preference for GSE securitization over balance-sheet retention or private securitization during this period. Conversely, in the post-GFC period, I find that Freddie Mac earns a positive, statistically significant \$0.012–\$0.020 risk-adjusted profit per \$1 of loan guaranteed.

On an annualized basis, this figure amounts to roughly a 30 bps risk-adjusted return, which exceeds Freddie Mac's annual 6–7 bps operating expenses needed to securitize the mortgages (Golding, Goodman, Parrott, and Ryan, 2023). These positive risk-adjusted returns are consistent with increases in guarantee fees and tightening of underwriting standards at the time and with the Federal Housing Finance Agency's (FHFA) goal for the GSEs to earn an adequate rate of return. However, these results imply that lenders are willing to pay an above-market rate for GSE guarantees in the post-crisis period.

One concern with the cash flow valuation approach is whether the selected market benchmarks truly replicate the risk profile of the underlying mortgage guarantees. To address this concern, I exploit Freddie Mac's Structured Agency Credit Risk (STACR) program, in which Freddie Mac sells synthetic securitization tranches to reinsure default risk from its guarantee book. In particular, Freddie Mac sells the subordinate tranches, whose market prices are observable, to market participants and retains the most "supersenior" tranche of the deal.[2] On average, the sold subordinate tranches comprise 4.25% of the total transaction size. However, these tranches are also the most risky and are expected to incur the most losses. For the most junior subordinate tranches, I find that the observed market prices imply the expected losses of $0.68 per $1 invested. In contrast, the sold senior subordinate tranches have average expected losses of $0.014 per $1 invested, because they have a much higher average initial credit enhancement of 3.2%. Intuitively, because the supersenior tranche has a larger amount of initial subordination than the senior tranche, one would expect a lower loss ratio for the supersenior tranche; however, the magnitude of these losses is an empirical question. By estimating the market price of the retained supersenior tranche, I can compute the total market value of expected losses of the underlying mortgage pool, which is a direct measure of the fair market cost of default insurance.

To measure the supersenior tranche prices, I estimate a loan-based structural model of default risk, building on Nagel and Purnanandam (2020), such that the model prices the riskier subordinate tranches correctly. I then extend this model to incorporate endogenous prepayment following Chernov, Dunn, and Longstaff (2018) and explicitly account for

[2] Additionally, Freddie Mac retains a vertical slice of the tranches, which are pari passu with the tranches sold to market participants.

prepayment timing across different loans and tranches. In particular, in STACR transactions, the most junior tranches are the first to incur losses and the last to receive unscheduled prepayments. However, if certain performance triggers are met, the subordinate tranches may receive prepayments pro rata rather than sequentially. I explicitly incorporate these features into the model. Applying this approach to STACR transactions from 2015 to 2023, I find that market participants require 27 bps annually to cover the expected losses on a typical Freddie Mac mortgage pool, which is roughly half of Freddie Mac guarantee fees during the same period.

If Freddie Mac charges an above-market price for mortgage guarantees in the post-crisis period, do banks reduce their loan sales to GSEs in response? A higher price of GSE guarantees could make it relatively more profitable for banks to simply hold the loans on their balance sheet since the market cost of funding is less than what Freddie Mac requires. Consistent with this idea, I document that banks reduce their loan sales to GSEs by 10pp following the increase in pricing. However, bank originators continue to sell over 40% of their loans to GSEs despite the above-market price, and their distribution of newly originated loans still exhibits bunching around the conforming loan limit, suggesting that there is still something valuable about using GSEs compared to other market-based alternatives. At the margin, higher guarantee fees prompt some banks to hold more mortgages on their balance sheets, but the costs of the alternatives may be sufficiently high that banks are willing to pay an above-market rate to securitize them through GSEs.

Why would banks continue to sell some loans to GSEs at an above-market rate rather than hold them on their balance sheet? One potential economic force is that lenders face balance sheet constraints that are sufficiently high compared to the rate that GSEs charge for insurance. To empirically test this idea, I examine how balance-sheet constraints affect lenders' GSE securitization behavior around changes in insurance pricing. First, I compare bank and non-bank lenders, which have limited ability to retain loans without the use of deposits. Second, within bank lenders, I examine variation in size, capital, and deposits. In particular, as shown by Buchak, Matvos, Piskorski, and Seru (2018a), banks receive considerably lower capital risk-weights for holding a GSE MBS rather than a whole loan on their balance sheet. Consistent with this notion, I show that more constrained lenders sell relatively more loans to the GSEs around increases in the GSE guarantee fee pricing. Following a 10 bps increase in guarantee fees, bank lenders are 20 pp less likely to sell conforming eligible loans to GSEs compared to nonbank lenders. Likewise, banks with more capital, more deposits, and larger size are all less likely to sell loans to GSES following an increase in pricing. Together, these results indicate that although some banks adjust their selling behavior at the margin, it is still optimal for many constrained lenders to continue selling to GSEs despite the above-market pricing.

I also present reduced-form evidence inconsistent with the GSEs providing a subsidy during the post-GFC period. It has been previously documented that, in the pre-crisis period, the jumbo–conforming rate spread was positive (e.g., Passmore, Sherlund, and Burgess 2005). A positive spread means that jumbo loans had higher rates than conforming loans, consistent with a GSE subsidy at the time. However, if GSEs began charging above-market fees for insuring credit risk after the crisis, then this jumbo-conforming spread should compress toward zero or even become negative. Using new HMDA data that covers the post-GFC period, I compare loans just above and below this conforming loan cutoff and find that interest rates are 10 to 20 bps lower for jumbo loans. A potential concern with this comparison, however, is that borrowers can choose the size of the loan they take out and, therefore, whether or not a loan is conforming or jumbo. To address this concern, I follow Kaufman (2014) and instrument jumbo loan status using a regression discontinuity design based on whether the home appraisal value exceeds 125% of the conforming-loan limit. Because appraisal values are exogenous to borrower choice and many lenders impose an 80% LTV constraint on balance sheet loans, loans with appraisals just above 125% are discontinuously more likely to have jumbo status. With this instrument, I confirm that jumbo bank loans have 10 bps lower rates than conforming loans in the post-crisis period. Moreover, I show that this negative spread appears only for bank originators, which have the option to retain loans. Nonbanks, which have limited balance-sheet capacity, do not exhibit a negative spread on their mortgages across the conforming loan limit. This reduced form evidence further corroborates that GSEs no longer subsidize mortgage rates and that lenders' balance sheet costs matter for lending decisions.

The evidence shows that GSEs price mortgage credit risk insurance above fair market values in the post-GFC period. Further, the market prices of STACR reinsurance notes demonstrate that there are private investors willing to bear this risk at prices below those set by the GSEs. Nonetheless, banks continue to rely on GSE securitization as their primary mortgage-funding channel. Although higher pricing has led banks to reduce their loan sales to GSEs, private-market securitization or balance sheet retention of GSE-eligible mortgages has not overtaken the standard model of selling these mortgages to GSEs.

Taken together, these facts suggest that, although recent GSE guarantee fees are no longer subsidized, lenders still capture net cost advantages by using GSEs to securitize mortgages over other market-based alternatives. Balance sheet costs, such as those induced by regulatory capital requirements, appear to play an important role. Under Basel III capital rules, agency MBS, which are backed by the implicit government guarantee of GSE credit risk, carry a 20% risk weight compared to 50% (or higher) for whole loans held on balance sheet. For large banks subject to stress testing under CCAR, the differential is more pronounced as agency MBS are largely exempt from credit loss scenarios. Banks would face simliar capital requirements issuing private market securitizations.[3] Likewise, for nonbanks, the results imply that the external financing frictions associated with raising private market securitization still exceed the price of the GSE securitization. In both cases, GSE securitization is valuable in part because it avoids these frictions, although the bank balance sheet costs may themselves be a product of regulation. Beyond balance sheet costs, lenders may also value operating cost efficiencies from GSEs' economies of scale and access to the liquid To-Be-Announced (TBA) agency MBS market, where the Federal Reserve conducts quantitative easing (QE) purchases. Additionally, even if guarantee fees are overpriced on average, GSE pricing may still offer cross-sectional subsidies for certain loan types.

The paper also has important implications for the policy discussion of GSE privatization. Although government-backed entities may be able to provide subsidized mortgage guarantees with below-market rates, such subsidies would not be sustainable for private shareholders who require market-rate returns. Although GSEs provided a subsidy in the precrisis period, the

[3] If banks were to replicate the GSE structure by securitizing the loans to private investors, they may still be expected to retain some of the issued tranches (Begley and Purnanandam, 2017), analogous to the vertical and horizontal slices Freddie Mac maintains in STACR. Under the Basel III securitization framework, retained junior tranches can carry risk weights of 1,250% while mezzanine pieces may carry risk weights of 200-650%.

findings show that the current GSE single-family guarantee book is economically profitable. A limitation of this analysis is that the estimates do not reflect how the market prices of risk might change or other general equilibrium-type effects should GSE privatization occur. For example, lenders' preference for GSE securitization may depend on the preferential regulatory treatment that agency MBS receive from their government-owned status. For instance, agency MBS may no longer be considered to have near-zero credit risk in capital exercises such as CCAR stress testing if they are privatized.

A limitation of this paper is that it focuses solely on measuring the subsidy banks receive from GSEs' pricing of guarantees on fixed-rate single-family mortgages. The findings in this paper do not speak to the valuation of other instruments on their balance sheet. For instance, GSEs purchased significant amounts of *subprime* MBS during the housing crisis (Richardson, Van Nieuwerburgh, and White, 2017). Studies by Passmore (2005), Lucas and McDonald (2006), and Lucas and McDonald (2010) analyze the total implicit subsidy to GSE shareholders using option prices and market comparison of their debt to similarly risky institutions. By focusing on cash flows of guarantees, this paper directly examines how much subsidy is passed to the *banks* that sell their mortgages with Freddie Mac guarantees. Delineating between the subsidies to GSE shareholders and subsidies passed to market participants matters for understanding how this government-sponsored intermediation contributes to the functioning of this market.

This paper contributes to several bodies of literature analyzing mortgage lending, securitization, and the role of the GSEs. This paper complements Bhutta (2012), Hurst, Keys, Seru, and Vavra (2016), Tsai (2023), and Gete, Tsouderou, and Wachter (2024), which analyze the *cross-sectional* mispricing in GSE loan guarantees across different demographics, geographies, and borrower characteristics. To the best of my knowledge, this paper is the first to measure the overall *level* of subsidy provided by GSEs on their loan guarantees by estimating their value from the perspective of public market investors. This paper also provides empirical evidence that can inform models that change or remove GSE guarantee subsidies, such as in Elenev et al. (2016) and Gete and Zecchetto (2018). This paper focuses on the credit risk differential between GSE and markets, which complements Fuster and Vickery (2015), which studies lenders' reluctance to absorb interest rate and prepayment risk from 30-year mortgages. The findings in Fuster and Vickery (2015) also offer another potential explanation as to why lenders continue to sell to GSEs despite charging an above market price to insure credit risk. This paper's results on the jumbo-conforming spread differential across banks and nonbanks also speak to recent developments in the GSE market in the post-GFC period and the rising role of non-bank intermediation in this market (e.g., Buchak et al. (2018a), Buchak, Matvos, Piskorski, and Seru (2018b), and Fuster, Plosser, Schnabl, and Vickery (2019)). I also contribute to the literature studying conforming-jumbo loan spreads (Passmore et al., 2005; Kaufman, 2014; DeFusco and Paciorek, 2017; Fisher, Fratantoni, Oliner, and Peter, 2021) by establishing a link between this spread and the valuation of GSE guarantees and applying an instrumental variable approach to estimate the spread in the post-crisis period.

The structural default risk model valuation in this paper is related to Golding and Lucas (2022) and O'Neill (2022), which study the risk and prices of GSE credit risk transfer (CRT) bonds using reduced-form approaches, and Gete et al. (2024) and Gete, Pavlov, Tsouderou, and Wachter (2025), which study the impact of climate risk and forbearance on market assessments of risk using CRT prices. Additionally, this paper makes a methodological contribution by incorporating endogenous prepayment following Chernov et al. (2018) into the Nagel and Purnanandam (2020) model. In contrast to this paper, which takes the prices CRT investors are willing to pay as given, subsequent work by Capponi, Van Nieuwerburgh, and Wu (2025) studies whether CRT bonds are mispriced relative to a model that prices Treasury and corporate bonds. Although Capponi et al. (2025) finds evidence of mispricing across CRT tranches, their model finds a similar market price to guarantee the underlying mortgages in the post-crisis period as in this paper.

This paper also relates to an extensive literature that focuses on the securitization and incentives of mortgage originators, securitization, and the role of nonbank lenders, including work of Keys, Mukherjee, Seru, and Vig (2010), Purnanandam (2011), Buchak et al. (2018a), Buchak et al. (2018b), and Fuster et al. (2019), among many others. Similar to this paper, Flanagan and Purnanandam (2024) assesses the magnitude of the subsidized funding that banks received from the TARP government bailout. Despite the extensive literature on mortgage financing, there is limited empirical evidence on quantifying subsidies from GSEs by risk-adjusting the returns from their loan guarantees, which is crucial to understanding the moral hazard that financial intermediaries face in offloading mortgages through securitization.

Finally, this paper has immediate implications for the policy assessment of GSE guarantee subsidies. Existing policy analysis has led to mixed conclusions about GSE subsidies. The FHFA and Congressional Budget Office (CBO) estimate GSE guarantee subsidies by using historical default rates of loan categories to project expected losses and discounting them using Treasury rates plus a chosen risk premium (Congressional Budget Office, 2018, 2025; Federal Housing Finance Agency, 2025). Using these methodologies, both the FHFA and CBO find that post-crisis guarantees are underpriced and offer a subsidy relative to their credit risk. In contrast, the cash flow risk-adjustment and Merton-style structural model in this paper explicitly estimates market prices of the guarantees that incorporate forward-looking risk premia and expected losses from the perspective of market participants. Consistent with this paper's findings, Freddie Mac (2017) reaches a similar conclusion that in the post-crisis period, g-fees exceed the market price of credit risk implied by STACR security prices. In contrast, Golding and Lucas (2022) argues that the cost of re-insuring through STACR bonds is likely expensive because this cost is sensitive to the level of unobserved riskiness of the retained senior tranche and its associated tail risk. This paper provides new methods for determining the overall subsidy by explicitly estimating the price of this tail risk using the model framework of Nagel and Purnanandam (2020) and modelling endogenous prepayment timing of the tranches to directly estimate the market value of the underlying guarantee cash flows.

1 GSE Policy and Institutional Background

Fannie Mae was created in 1938 as a part of Franklin D. Roosevelt's New Deal and, at the time, was owned entirely by the government. To address homeownership during the Great Depression, Fannie Mae introduced the 30-year mortgage and had a policy objective of promoting "liquidity, stability, and affordability" by purchasing and holding mortgages in its portfolio.[4] Later, in 1968, Fannie Mae was restructured as a private but government-sponsored

[4]For a complete history of Fannie Mae, see https://www.fanniemae.com/about-us/who-we-are/history

enterprise. Despite being private, this association with the government meant it benefited from lower funding costs due to implicit government backing. In 1970, Freddie Mac was created and began to securitize the conventional mortgages it purchased into MBS, creating a liquid secondary market for mortgages. In 1980, Fannie Mae also began securitizing its mortgages into MBS rather than only holding the mortgages in their portfolio.

The typical contract GSEs still offer today was introduced when Fannie Mae began securitizing mortgages. GSEs maintain a set of eligibility criteria for mortgages they will purchase using characteristics such as LTV, debt-to-income, and credit scores. GSEs then bundle the mortgages into MBS, insure the credit risk of the MBS, and sell the resulting securities to market investors. Lenders can either sell their mortgages at the 'cash window' and receive money upfront using prevailing To-Be-Announced (TBA) prices of MBS or through the 'swap channel' in which lenders receive MBS guaranteed of any credit risk in exchange for selling the mortgages (An, Li, Liu, and Song, 2022). In order to sell their mortgages to GSEs through either channel, lenders must purchase credit risk insurance from the GSEs by paying a 'guarantee fee' or 'g-fee.' Additionally, lenders retain the servicing rights to the loans and are paid a residual cash flow to forward the principal and interest to the MBS bondholders. The guarantee fee is a type of insurance premium GSEs use to cover losses on interest and principal on the MBS bondholders when the underlying mortgages become delinquent or default. As a result, the MBS holders bear interest rate and prepayment risk, and the GSEs bear the corresponding credit risk of the mortgages.

The primary function of the GSEs has been to purchase, insure, and securitize conventional 30-year mortgages. However, during the subprime crisis, the GSEs expanded their role and began purchasing Alt-A and subprime MBS, holding them on their balance sheet, and financing them with debt that had perceived government backing (Richardson et al., 2017). Due to their thin equity position and large losses from these riskier mortgage purchases during the GFC, they were placed into government conservatorship in September 2008 (Richardson et al., 2017). Following the GFC, the FHFA sought to improve the profitability of the GSEs and make them more competitive with private capital markets. As a step in this direction, the GSEs began reinsuring some of the mortgage guarantee default risk to private capital markets through credit risk transfer (CRT) programs in 2013, such as Freddie Mac's STACR transactions, with the goal of reducing taxpayer exposure to this risk. The GSEs remain in conservatorship; however, recent policy discussions have emerged around privatizing the GSEs again.

2 Data & Methodology

2.1 Freddie Mac Loan Guarantee Cash Flows

To value the GSE loan guarantees, I estimate the present value (PV) of the net cash flows Freddie Mac receives from the guarantee contract with loan originators/sellers. To compute the cash flows GSEs receive on their guarantees, I follow the decomposition in Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013).[5] I also use this decomposition to show how GSE guarantees relate to the cash flows that borrowers pay and lenders receive. Upon receiving a mortgage, borrowers pay principal P_t and interest payments $r_{note,t}$. When lenders then sell their mortgages to GSEs, they agree to pay a negotiated g-fee rate $r_{gfee,t}$ on the outstanding balance of loans, receive residual servicing rights cash flow $\sigma_{servicing,t}$, and receive a MBS insured from any credit risk that pays $r_{coupon,t}$ and is valued at $TBA(r_{coupon,t})$ in the TBA market.[6] The resulting relationship between the mortgage rates borrowers pay and the MBS coupon rate is:[7]

$$r_{note,t} = r_{coupon,t} + r_{gfee,t} + \sigma_{servicing,t}.$$

After extending a given $LoanAmt$ to a borrower, the corresponding value a lender receives for selling that mortgage to the GSEs is:

$$PV(\sigma_{servicing,t}) + TBA(r_{coupon,t}) - PV(r_{gfee,t}) - LoanAmt.$$

[5]Without any loss of generality, the below example ignores upfront fees paid by borrowers.

[6]Or identically, they receive the value of $TBA(r_{coupon})$ if using the cash window. Because the resulting MBS bond is free of credit risk, the bond pricing in the TBA market only reflects the interest rate of the coupons and the prepayment risk of the underlying mortgages.

[7]Lenders exercise some discretion in substituting a lower coupon rate on the MBS they receive for a higher servicing rights cash flow (Fuster et al., 2013).

As shown in Fuster et al. (2013), the value of the above term has been rising recently, suggesting that lenders need higher returns to cover the higher intermediation costs of making mortgages.

If a loan goes into default or becomes delinquent, Freddie Mac must continue to send interest to bondholders even if the borrower does not pay their mortgage note. Because GSEs bear this risk, the present value of any defaults on mortgages' unpaid principal balance (UPB) plus any other delinquent accrued interest, $PV(P_t^D + r_t^D)$, (net of any recoveries) is a cost borne by the GSEs in exchange for receiving the associated g-fees. The GSEs' present value of this insurance contract is the main economic object of interest in this paper:

$$PV(GSE\_Guarantee_t) = PV(r_{gfee,t}) - PV(P_t^D + r_t^D). \quad (1)$$

If the NPV of the net guarantee cash flows is zero, this means that the insurance premiums from guarantee fees exactly cover the expected financial costs of paying any claims and that there is no subsidy.[8]

To estimate the value of GSE mortgage guarantees, I need both the g-fee cash flows that GSEs receive from lenders and the cash flows that GSEs forward to MBS bondholders when mortgage borrowers default or are delinquent. Additionally, if a borrower defaults, GSEs limit their losses by recovering some of the UPB by selling off the house as collateral and requiring borrowers with high LTVs to purchase private mortgage insurance. Combining the g-fees, the mortgage losses, and the asset recovery into a single cash flow term, I write the net cash flows from GSEs guarantees at any point in time as:

$$GSE\_cf_t = r_{gfee,t} - \mathbb{1}_{Default}[P_t^D - Recoveries_t + r_t^D]. \quad (2)$$

I apply the methodologies described in the risk-adjustment section to value these net cash flows to estimate $PV(GSE\_Guarantee) = PV(GSE\_cf_t)$. I describe the data sources for computing the net cash flows in the section below.

[8]The complete relationship between the value of the underlying mortgages, the value of the credit-risk-free MBS, the value of servicing rights, and the value of the defaults/ delinquent interest is $PV(P_t + r_{coupon,t}) = PV(\sigma_{servicing,t}) + TBA(r_{coupon,t}) + PV(P_t^D + r_t^D)$. This relationship follows from the splitting of the cash flows in the securitization process.

Default, Recovery, and Delinquent Interest: I use the Freddie Mac Single Family Performance Dataset to compute the default, recovery, and delinquent interest portion of the guarantee cash flows in the above Equation (2). The key advantage of the Freddie Mac data set, unlike Fannie Mae's Single Family Performance Data, is that it is selection-bias-free and includes all mortgages in its guarantee book since 1999.[9] In contrast, the Fannie Mae data set only reports the performance of loans that resemble those that meet its current underwriting standard.[10] This dataset offers detailed information on loan performance, starting with loans originated in 1999, and reports the exact amount of loan losses and forbearance losses covered by Freddie Mac's guarantees and owed to MBS bondholders.[11] I end the sample with loans originated in 2018 in order to have a sufficiently long time series to completely observe the guarantee cash-flow realizations. Most of the outstanding loan principal on loans originated prior to 2018 was paid down by 2024Q4, the final period for which I have collected realized cash-flow data. I limit the sample from this dataset to only cover fixed-rate single-family mortgages.

Guarantee-Fees: To get the guarantee fee part of the cash flows, I follow Fuster et al. (2013) and use Freddie Mac's 10-Ks and annual reports to determine the average effective guarantee fees for new single-family acquisitions, which is plotted in Figure 3.[12] After April 2012, there was a 10 bps statutory increase in g-fees due to the Temporary Payroll Tax Cut Continuation Act of 2011. These 10 bps are effectively a tax sent to the Treasury, but they are still part of the total cost lenders must pay to obtain GSE guarantees. Lenders could avoid this tax entirely by retaining loans on their balance sheet or using private securitization, so including it matters for whether the GSE pricing lenders pay is fair relative to market-

[9] In the Appendix, I report the results from using the Fannie Mae Single Family Performance data set.

[10] In particular, Freddie Mac reports data on both "standard" mortgage performance and "non-standard" mortgage performance, which no longer conform with their current underwriting standards and performed significantly worse during the GFC. Fannie Mae only reports the performance of "standard" mortgages in their single-family performance data set. For more information, see: https://capitalmarkets.freddiemac.com/crt/docs/docs/sflld_nsd_summary.pdf.

[11] In particular, the data set reports the "Actual Loss", which is the UPB plus delinquent interest minus any recoveries and credit enhancements (e.g., proceeds from requiring borrowers to use PMI), and "Cumulative Modification Cost", which is the amount of interest cost borne by the guarantees from having to forward interest to MBS bondholders when a loan is placed into forbearance. The complete data dictionary is available at https://www.freddiemac.com/fmac-resources/research/pdf/user_guide.pdf

[12] The reported guarantee fees are 'effective' because lenders can partially 'buy down' the recurring premiums in exchange for a one-time fixed payment. The total effective g-fees are reported on an annualized basis in Freddie Mac's annual reports.

based benchmarks. Because this tax went into effect after GSEs entered into government conservatorship, the total guarantee fees, including the 10 bps tax, can also be interpreted as the total cash flows to the consolidated government balance sheet. In the post-crisis period, GSEs introduced differential guarantee pricing on loans based on a matrix of loan characteristics. Because the main empirical exercise is to value the overall guarantees offered by GSEs, I simply use the average guarantee fees on the guarantee book to perform the cash flow valuation.

Guarantee Cash Flow Vintages: I sum the guarantee cash flows into portfolios based on the quarter in which those loans originated. Because cash flows have both a vintage t dimension and each vintage has multiple horizons h of cash flows after origination, I update GSE net cash flows notation as $GSE\_cf_{t,t+h}$. I divide these raw cash flows by the total loan amounts covered by the guarantees, meaning that the PV of the cash flows measures the profit per dollar of loan insured. To measure the aggregate subsidy provided by Freddie Mac on its loan guarantees, I report the value-weighted results in the baseline table, adjusting for the fact that the volume of loans originated varies over time.

Cash Flow Summary Statistics

Table 1 presents summary statistics on the net guarantee cash flows for mortgages originated from 1999 to 2018, spanning 80 quarters of data. Realized cash flows extend through 2024Q2, capturing both the Global Financial Crisis (GFC) and the COVID-19 pandemic. On average, Freddie Mac insured \$63 billion in mortgages each quarter, with the outstanding balances having an average weighted life of 4.2 years, reflecting the substantial prepayment of 30-year fixed-rate loans. In nominal terms, Freddie Mac collects \$130 million more in premiums than it pays out for losses, on average. At the end of the distribution, the worst quarter of originations saw \$4.9 billion more in losses than premiums, whereas the best quarter of originations had \$2.62 billion more in premiums than losses. Over the sample, the guarantee fee averages 32 basis points, ranging from 19 to 57 basis points.

Discounting these net cash flows by the risk-free term structure yields a "risk-free" present value of \$0.004 per dollar of loan guaranteed, or about \$263 million in each quarter on a present-value basis. The central question is whether this value remains positive once risk premia are taken into account.

Figure 2 plots the average cash flow distribution over time. Net cash flows are generally positive in the first few years after origination, but become negative beginning around year six when defaults emerge from problem loans once most of the principal has already been paid down. Any cash flows occurring after year 16 are discounted back to year 16 using the term structure of risk-free rates following Gupta and Van Nieuwerburgh (2021).

2.2 Structured Agency Credit Risk (STACR) Data

For the valuation exercise using the prices of Freddie Mac reinsurance tranches, I collect data on STACR tranches. Using STACR prospectuses, I collect the interest rate spreads, credit enhancement attachment points, detachment points, and CUSIPs for 55 STACR transactions originated over 2015 - 2023 from the Freddie Mac website.[13] I obtain the market prices for these notes in the month after their issuance from TRACE.

2.3 HMDA and Other Bank Data

I use HMDA data to investigate reduced-form evidence on the pricing of loans across conforming and nonconforming loans and banks' decisions to sell loans to the GSEs.

Pre-2017 HMDA: I use the HMDA dataset to investigate how banks change their likelihood of selling mortgages to GSEs around the increase in guarantee fees. Because of the size of the dataset when including multiple vintages, I use a 10% random sample.

Post-2017 HMDA: The updated HMDA dataset that begins covering loan originations in 2017 provides more detail than the original HMDA dataset. In particular, this updated dataset contains information on loan interest rates. I use this dataset to estimate the conforming-nonconforming loan spread.

MIRS: To measure the nonconforming-conforming loan spread in years prior to 2017, I use the Monthly Interest Rate Survey (MIRS) data provided by the FHFA.

FRY-9C: I gather bank sheet information, including bank size, tier 1 capital, and deposits, on the bank holding companies of lenders reporting in HMDA from FRY-9C. I follow the

[13]The data on the tranche is available at https://capitalmarkets.freddiemac.com/crt/securities. I only collect data on DNA and HQA "actual loss" transactions, for which the writedown of subordinate tranches depends both on the default rate and the loan recovery amount.

procedure in Loutskina and Strahan (2009) for merging call report and HMDA.

2.4 Risk-Adjustment Methodology

The risk of default/delinquency in the GSE guarantees means that the net cash flows in these contracts are risky and that any valuation must appropriately account for this risk. To discount these cash flows appropriately for their risk, I employ cash flow discounting methods developed in the private equity context. Specifically, I use the Korteweg and Nagel (2016) GPME methodology and the Flanagan (2025) and Gupta and Van Nieuwerburgh (2021) RAP methodology to value these cash flows. I describe both methodologies below in detail.

GPME

Specifically, I use the Korteweg and Nagel (2016) GPME methodology to estimate a stochastic discount factor (SDF) that correctly prices public market benchmarks with similar risk and cash flow distribution timing, and use this SDF to price the guarantees.

The first method I use to measure the risk-adjusted value of the GSE insurance contracts is the generalized public market equivalent (GPME) approach of Korteweg and Nagel (2016). The GPME methodology involves estimating a stochastic discount factor (SDF) of the form:

$$m_t = exp(a - b * r_t).$$

This SDF is estimated to correctly price capital market benchmarks with similar risks and cash flow distribution timing as the GSE guarantees. The resulting SDF can then be used to price the cash flows of interest, the GSE guarantees. Because the SDF is constructed to price these benchmark assets correctly, it will, therefore, correctly price the risk embedded in the guarantee cash flows that are spanned by these benchmarks. Additionally, an advantage of GPME for pricing insurance-like contracts is that the SDF is constructed to be strictly positive, meaning that it restricts arbitrage opportunities when pricing contracts with nonlinear payoffs (Korteweg and Nagel, 2016; Cochrane and Saa-Requejo, 2000). To apply GPME to valuing GSE guarantees, I calibrate the SDF to price test assets, described below, that span the relevant risk factors in GSE guarantees and instrument it with the outstanding principal balance of GSE mortgage guarantees following the Gredil, Sorensen, and Waller (2019) implementation of GPME. I then use the estimated SDF to discount the net guarantee cash-flow distributions normalized to a \$1 of loan guaranteed:

$$GPME = \frac{1}{T}\sum_{t=1}^{T}(\prod_{t}^{h} m_s) * GSE\_cf_{t,t+h}. \tag{3}$$

Risk-Adjusted Profit

Next, I apply the Flanagan (2025) implementation of the Risk-Adjusted Profit (RAP) framework (Gupta and Van Nieuwerburgh, 2021) to the GSE contracts. The core insight from Gupta and Van Nieuwerburgh (2021) is that privately held assets—whose market values are not directly observable—can be priced by constructing replicating portfolios from publicly traded benchmarks. The market value of these replicating portfolios can then be used to price these non-traded cash flows. Building on this idea, Flanagan (2025) develops benchmarks specific to debt-like cash flows, relying on the law of one price to construct benchmarks without the need for an explicit asset pricing model.

Because the GSE guarantees' cash flows include insurance premiums (analogous to loan interest payments) and policy claims (effectively loan defaults), the Flanagan (2025) methodology applies directly. The only distinction between loan cash flows and mortgage insurance guarantees cash flows is the absence of principal repayments. Similar to Flanagan (2025), the declining balance on each guaranteed loan over time allows one to construct instrumented "gain benchmarks" from Flanagan (2025) by weighting investments in public securities according to the fraction of outstanding principal. This time-varying exposure helps capture the non-linearity of the payoffs. Following this methodology, I estimate

$$GSE\_cf_{t,t+h} = a_{t+h} + \sum_{k=1}^{K}[c_h^k \tilde{G}_{t+h}^{i,k}] + e_{t+h}^i. \tag{4}$$

I compute the corresponding present value of the GSE cash flows by taking the present value of both sides. By the law of one price, if the benchmarks on the right-hand side span the relevant risk on the left-hand side, then the benchmarks' market prices are equal to the market prices of the cash flows, and the residuals are correctly valued at mean zero.

Factor Selection

For both the GPME and RAP approaches, I select benchmarks to capture the key price risk factors embedded in the loan guarantee cash flows. Below, I summarize these chosen benchmarks.

Interest Rate Risk: The horizon intercept coefficients a_{t+h} in Equation (4) correspond to investing in risk-free zero-coupon bonds of varying maturities that are discounted back using the term structure of Treasury bond yields of corresponding maturities.

Market Risk: To account for aggregate risk and broad equity-related risk, I include the CRSP value-weighted market return.

Credit Risk: An ideal benchmark for mortgage default risk would be returns from securities directly investing in mortgages. The closest such security during the sample period is the tranches of private label/nonagency securitizations, which, unlike agency MBS, are not insured from default risk. However, market price and return data for these securities are largely unavailable before TRACE reporting began covering them in 2013. Nonagency mortgage REITs (mREITs) provide an appropriate alternative benchmark, as they maintain leveraged positions in these nonagency securitizations and offer readily available market data throughout the sample period. Using the list of nonagency and hybrid mREITs identified in Pellerin, Sabol, and Walter (2013), I compute their value-weighted returns from CRSP data. Additionally, I incorporate the Nareit REIT index returns following Gupta and Van Nieuwerburgh (2021) to capture broader real estate risk exposure

3 Results

3.1 GSE Guarantee Cash Flow Valuation

I start by estimating the risk-adjusted valuation of the GSE loan guarantees covering mortgages originated and insured over the full sample period, 1999-2018. I present the estimates of $PV(GSE\_Guarantee)$ using both the GPME methodology and the RAP methodology to appropriately discount the cash flows according to their riskiness. I report both equal-weighted and value-weighted estimates of the guarantee cash flows. However, I focus on the value-weighted results in the exposition because these determine the overall value of the guarantees.

Generalized Public Market Equivalent (GPME)

Table 2 contains the valuation estimates using the GPME approach. Panel A contains the equal-weighted estimates, and Panel B contains the value-weighted estimates. Across the Columns (1)-(3), I estimate GPME using each of the risk factors separately and in Column (4) I estimate a specification that includes all three risk factors.

Column (1) estimates a version of GPME that prices the risk-free and the stock market portfolio correctly, analogous to the CAPM. The estimation finds similar SDF parameters for the same specification as in Korteweg and Nagel (2016). On an equal-weighted basis, the corresponding estimate of $PV(GSE\_Guarantees)$ is statistically indistinguishable from zero with a PV $0.001 per $1 of mortgage guaranteed. On a value-weighted basis, the same figure is effectively zero. The estimate means that, on average, GSEs charge a fair price to insure mortgage default risk rather than provide a subsidy that would imply a negative valuation.

Next, I expand the set of risk factors to include priced benchmarks with relevant mortgage credit risk, including REIT and nonagency MREIT factors. Columns (2) and (3) show similar estimates with these risk factors. Including all three factors into the estimation in Column (4), I find similar point estimates as in the first specification – I find a valuation indistinguishable from zero on an equal-weighted basis. These findings contradict the premise that GSEs, on average, provide a credit risk subsidy on their conventional mortgage guarantees.

Risk-Adjusted Profit

Table 3 presents the risk loadings and risk-adjusted valuations following the RAP methodology. Panel A reports the risk loadings from estimating Equation (4) with cash flow horizons out as far as 16 years after the loans were originated. The guarantee cash flows load positively on both the CRSP VW stock market index and on the nonagency MREIT benchmark returns. These loadings confirm the intuition that cash flows of the GSE credit risk insurance are exposed to both aggregate risk and mortgage-specific risk factors.

Panel B of the table presents the estimates of the valuation of the GSE guarantees by using market prices of the replicating portfolio implied by the factor loadings in Panel A. The RAP methodology finds that Freddie Mac earns $0.002 per $ 1 of loan guaranteed on an equal-weighted basis and $0.002 per $ 1 guaranteed on a value-weighted basis. Again, neither estimate is statistically different from zero. These findings reinforce the earlier evidence that, on average, GSEs break even on their conventional mortgage guarantees.

Pre- and Post-Crisis Valuations

Next, I estimate the PV of GSE guarantees for subsamples of loans originated before and after the Global Financial Crisis using 2010 as a cutoff year. This analysis is motivated by the sharp change in the GSE pricing of guarantees following the GFC, as shown in Figure 3. For this exercise, I report the value-weighted guarantee valuations. The results are described in Table 4.

Table 4 shows that in the pre-GFC period, the value of the GSE guarantees is negative and statistically significant for both methodologies. The point estimate is -$0.009 per $1 of loan guaranteed, meaning that on an annualized basis, Freddie Mac provided a guarantee fee subsidy of approximately 20 bps in the pre-crisis period. The evidence shows that in the pre-crisis period, GSEs used their government-backed funding to provide credit risk subsidies to mortgage originators. This finding is consistent with banks' strong preference for selling mortgages to GSEs rather than holding them on their balance sheet.

In the post-GFC period, however, both estimates are positive and highly statistically significant, with point estimates of $0.012 and $0.020 for GPME and RAP, respectively. These estimates show that Freddie Mac began to no longer provide a subsidy after the GFC and even began to earn a risk-adjusted profit. After the crisis, Freddie Mac's stricter underwriting guidelines reduced underlying mortgage credit risk while higher guarantee fees boosted revenues. As a result, Freddie Mac incurred minimal losses even during the COVID-19 pandemic, leading to substantial risk-adjusted profits rather than a subsidized cost of credit. GSE's operating expenses are approximately 7 bps (Golding et al., 2023). Although the financial cost of the guarantees seems to be fairly priced, even after paying expenses, these estimates still suggest that GSEs charge an above-market price for their guarantees in the post-crisis period.[14]

[14]Subtracting these operating expenses from the risk-adjusted returns likely represents a conservative estimate of the excess costs banks pay to use GSEs. These 6-7 bps in administrative expenses are costs that banks avoid if they retain their loans on the balance sheet instead of securitizing through GSEs. This is because banks typically service loans regardless of whether they are retained as whole mortgages or sold and held as MBS plus servicing rights. Therefore, banks incur administrative expenses for servicing these loans regardless of whether GSE securitization is used. Subtracting these expenses, however, may be appropriate when considering private securitization as the alternative benchmark, which does require additional administrative expenses.

3.2 Valuation Using Market Prices of GSE Reinsurance

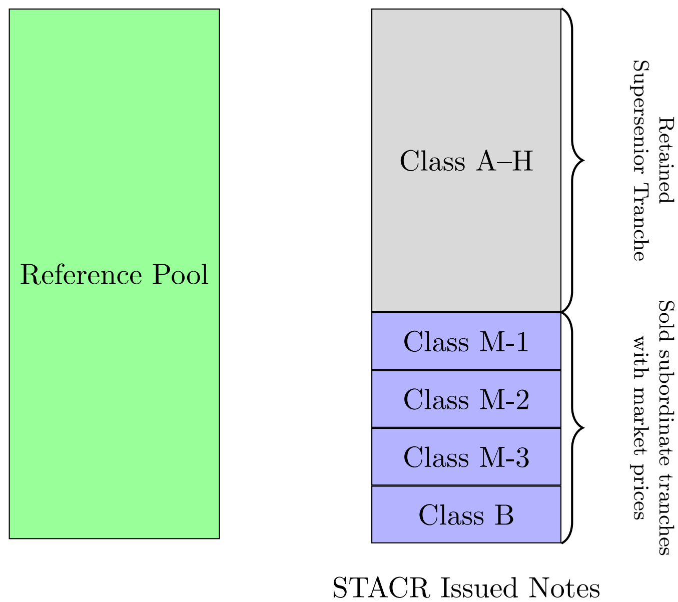
There are two potential concerns with the cash flow valuation analysis so far. The first concern is that the market benchmarks used do not fully capture the risk factors needed to form a replicating portfolio of identical risk as the underlying mortgage guarantees. Relatedly, although the realized guarantee cash flows have in-sample default shocks from the GFC and the Covid-19 pandemic, there is a concern that there is still some omitted tail risk because the sample does not have a sufficiently long time series. To address these issues and develop a market price of security with identical risk as the guarantees, I exploit the fact that Freddie Mac sells synthetic securitization tranches that effectively reinsure the underlying mortgage default risk from their guarantee loan book through the Structured Agency Credit Risk (STACR) program. The STACR program began in post-crisis period and allows for an alternative benchmark for the market price of insurance in this period. Figure 1 below illustrates the typical structure of a Freddie Mac STACR deal.

For each STACR transaction, Freddie Mac selects a subset of their guarantee mortgages and assigns them as assets on the STACR balance sheet. As in a typical mortgage securitization transaction, the securitization vehicle then issues notes with varying seniorities that are "backed" by these mortgages. The most junior tranches, Class M-1, Class M-2, Class M-3, and the first loss Class-B notes, typically absorb the first 5% of losses from the reference loan pool in exchange for receiving a coupon to compensate for the potential losses. If the underlying mortgages perform well and do not realize significant losses, then these subordinate notes will pay back their principal and coupon; however, if the mortgage pool realizes enough losses, the notes will begin to be written down in reverse order of seniority.[15] These subordinate tranches are sold to market participants and therefore have traded market prices. Freddie Mac then retains the "supersenior" A-H tranche. Freddie Mac also retains a vertical slice across the sold subordinate tranches. The entire transaction is "synthetic." This is because, although Freddie Mac pays the note holders based on the underlying mortgage performance, the mortgages do not actually back the notes. Instead, the mortgages are used as "real"

[15] In contrast, the most senior tranches receive principal payment first, and the subordinate note holders are the last to have principal repaid, meaning that the subordinate tranches are less affected by prepayment and have a longer effective maturity than the underlying mortgages.

collateral elsewhere in agency MBS. Additionally, the traded notes are floating rate whereas the underlying mortgages are fixed rate. Unlike CDS or other credit derivative products, STACR bonds are free of counterparty risk because the investors purchase the bonds upfront and the principal is written down when losses are incurred.

Figure 1: Freddie Mac STACR capital structure. Left: underlying mortgage pool (green). Right: sold subordinate tranches (light-blue) and retained supersenior (gray).



The economic object of interest from this transaction is the market value of expected losses on the underlying mortgage pool. When annualized, this measure corresponds to the fair market price to insure the pool from default risk.[16] The market price of insurance can then be directly compared to what Freddie Mac actually charges to insure these mortgages through their guarantee fees.

Although the subordinate notes that are sold to market participants only represent around 5% of the principal balance of the total underlying mortgage pool, they bear most of the expected losses because they are the junior claimholders. The sum of the market prices of these tranches, therefore, provides a nearly complete picture of the market value of expected losses for the underlying mortgage pools. However, what is still needed is a market price of the retained supersenior tranche, which is not sold to market participants. By utilizing the

[16]To see this, a fairly price insurance contract requires that the PV of insurance premiums plus the market value of expected losses equals zero.

traded prices of junior and mezzanine tranches, which are the first to absorb losses from the reference pool, this approach explicitly incorporates market-implied tail risk to discipline the valuation of the retained supersenior tranche.

I handle the market price of the supersenior tranche in two ways. First, I compute the market value of expected losses using the simplistic assumption that the expected losses on the supersenior tranche are negligible and completely absorbed by the subordinate tranches.[17] Second, I estimate a structural model of default risk such that the model exactly prices the subordinate tranches correctly, providing a market price of the supersenior tranche and therefore the total market value of expected losses. Because the underlying assets of the securitization are loans, I follow the model in the Nagel and Purnanandam (2020), which modifies Merton (1974) to account for the case when firm assets are loans. Intuitively, even if there is enough tail risk that the supersenior tranche is not risk free, the subordinate tranches are first exposed to losses, meaning that they help put a bound on the market price of the tranches, and the structural model provides discipline by constraining the distribution of losses across tranches based on their seniority in the capital structure.

3.2.1 Default Free Supersenior Tranche Implementation

First, I describe how I compute the market value of expected losses when I assume that the supersenior tranche is default-free. The STACR notes each promise a coupon at a spread over the 1-month LIBOR rate. Therefore, to back out the market price of the expected losses for each tranche, I subtract the present value of their expected coupon spread in the absence of default.[18] With the market prices of expected losses for each tranche, I simply add them

[17] Golding and Lucas (2022) takes a similar approach to analyzing CRT transactions by taking a weighted average of the tranche spreads and making different assumptions about the A-H tranche spread.

[18] I estimate the PV of the expected coupon spread for each tranche using the continuous time approximation:

$$c\int_0^T e^{-r\,t}\,dt = c\,\frac{1-e^{-rT}}{r}\,. \tag{5}$$

Because of prepayment in the underlying loan pool and because senior tranches are repaid first, each tranche will have a different effective maturity, T. To accurately capture the maturities expected by investors for each tranche, I set T to the take the risk-free weighted average life (WAL) described in the STACR prospectuses that corresponds to a constant prepayment rate (CPR) of 15%. For example, see: https://capitalmarkets.freddiemac.com/crt/docs/legal-documents/stacr/series-2016-dna1/16_dna1_0720281sto.pdf This approach is conservative as the CPR of mortgages was closer to 25% over the sample period. If investors require an additional risk-premium for prepayment risk, this approach will overstate the expected losses of and annualize them using the expected weighted average life of the underlying mortgage balances, 4.2 years, to arrive at the fair market price of insurance for the loan pool.[19] For some STACRs deals, Freddie Mac retains a small slice (around 0.5% of the loan pool) of superjunior Class-B notes, for which I do not have a market price. When this is the case, I make the very conservative assumption that this superjunior tranche is always completely wiped out and therefore has an expected loss of 100%.

3.2.2 Structural Default Risk Implementation

Turning to the structural default risk estimation, I build on the "single cohort" model framework of Nagel and Purnanandam (2020).[20] In their model, the payoff of an individual loan, L_T^i, with maturity T is written as a short put option on some underlying collateral, A_T^i, with a strike price of the promised face value of the loan F_T^1 due at maturity:

$$L_T^i = min[A_T^i, F_T^1]. \tag{6}$$

The collateral value underlying each loan, A_T^i, follows a geometric Brownian motion with a Vasicek (1991) systematic shock to all borrowers as well as an idiosyncratic shock:

$$\frac{dA_t^i}{A_t^i} = r\,dt + \sigma\Big(\sqrt{\rho}\,dW_t + \sqrt{1-\rho}\,dZ_t^i\Big). \tag{7}$$

Importantly, A_T^i is the latent collateral value backing the loan, with drift and volatility estimated jointly from CRT prices, rather than observed house prices.[21] The total loan pool

credit risk. This is because the expected value of the promised coupon spread will be lower if using a higher discount rate. After subtracting, the remaining market price of expected losses will be higher.

[19]This is the realized weighted average life of 4.2 years from the mortgage cash flow data.

[20]In general, they model banks' assets as consisting of multiple cohorts of loans of varying origination vintages. A securitization balance sheet consisting of loans originated at the same point in time corresponds to the special single-cohort case.

[21]For example, the collateral value can conceptually be written as $A_t^i = P_t^i + W_t^i$, where P_t^i is the house value and W_t^i is a non-house wedge reflecting pledgeable human capital, non-pecuniary occupancy value, and the option value of continued payment associated with the rent-price wedge, as documented in Loewenstein and Willen (2023) and Loewenstein, Willen, Yao, and Zhang (2025). The pure-house special case $W_t^i = 0$, implicit when observed house prices are fed in as the collateral process predicts default the moment a borrower has negative equity, counter to the evidence in Bhutta, Dokko, and Shan (2017) that borrowers only walk away once deeply underwater. Because μ and σ are estimated rather than imposed, W_t^i need not be specified explicitly.

value L_T payoff across individual loans at maturity can then be computed by integrating over all borrowers i and across different realizations of Brownian motion shocks. Let F_T^2 denote the total promised amount of the loan pool. At maturity, the fraction of realized loan losses as a fraction of the total promised loan pool can be written as:

$$Loss_T = (L_T - F_T^2)/F_T^2 \tag{8}$$

This loss rate is needed to determine the payoffs to the subordinate tranches sold to market participants by Freddie Mac. The key feature of the subordinate tranches is that they have an initial attachment point and a detachment point, which determine when they begin to absorb losses and when they stop covering a given level of losses. For instance, a tranche with a 0% attachment point and 1% detachment point is a first-loss piece, meaning that the first dollar of losses on the loan pool is borne by this tranche. The principal balance of this tranche would be (d-a) = $0.01 on a $1 loan pool and is completely written down if loan payoffs fall below 99% of the promised loan amount $L_T < (1 - .01) * F_T^2$. Likewise, a tranche with a 1% attachment point and 3% detachment point does not take any losses until the first loss piece below it is exhausted, but only takes the next 2% of losses up to the point where $L_T < (1 - .03) * F_T^2$. The principal balance of this tranche would be $0.02 on a $1 pool. Each subordinate tranche pays a spread coupon of y on its principal balance; however, the principal balance is written down as the underlying losses on the loans grow.

The total payoff to a tranche that attaches at a and detaches at d at maturity T can be written as follows:

$$Tranche_T^{a,d} = \exp((r+y)*T)*(d-a)+\exp((r+y)*T)*min[max[Loss_T+a,(a-d)],0]). \tag{9}$$

This equation states that if the tranche is responsible for no credit enhancement losses, it simply pays the coupon on the tranche principal balance. If the loss ratio exceeds the detachment point d level of credit enhancement offered, then the tranche is completely wiped out. If the level of $Loss_T$ lies between a and d, then the tranche is paid a fraction of its principal and coupons. The present value of the tranche at the time of origination is computed by taking the risk-neutral expectation and discounting back to the present with $exp(-rT)$:

$$Tranche_0^{a,d} = \exp(-r * T) * E^{\mathbb{Q}}[Tranche_T^{a,d}]. \tag{10}$$

To estimate the model, the initial market value of collateral A_0, the asset volatility σ, and the loan pool correlation ρ are the key parameters that determine the distribution of the underlying collateral value and pin down the market prices of the tranches. To solve for these three unknowns, I estimate the model for each STACR transaction so that it correctly prices the two most senior subordinate tranches and the most junior tranche using the pricing data from TRACE just after the transactions are offered.[22] For the other model parameters, I normalize the total book value of the loans to $1 and use the 10-year Treasury bond as the risk-free rate in the model and set $T = 10$, which is the typical WAL of the most junior tranches.[23] As in the previous case, I first back out the market price of expected losses of each tranche by subtracting the present value of their coupon spreads from the TRACE price. Within the model, I then set the mortgage and tranche spreads to zero and estimate model prices to match these coupon-adjusted prices. This approach effectively treats the STACR tranches as credit derivatives that pay only the risk-free rate and potentially incur losses. The resulting prices reflect only the expected market losses from default risk. After computing the model's market value of expected losses of the loan portfolio, I annualize it using the shorter average 4.2 WAL of the loan pool that I find in the data, as shown in Table 1.

Endogeneous Prepayment

To incorporate endogenous prepayment into the model, I introduce a stochastic interest rate process (Vasicek, 1977):

$$dr_t = \kappa_r\big(\theta_r - r_t\big)\,dt + \sigma_r\,dW_t. \tag{11}$$

The revised asset process follows this interest rate path and shares the same aggregate shock,

[22] I follow Nagel and Purnanandam (2020) and obtain the moments from the model using 10,000 draws, and I solve the model using multi-start simulated annealing with 500 starting points.

[23] Because subordinate tranches' principal balances are repaid last within the securitization, the subordinate tranche WALs will be longer than those of the underlying loan pool. I model this explicitly in the endogenous prepayment version of the model described below.

dW_t:

$$\frac{dA_t^i}{A_t^i} = r_t\,dt + \sigma\Big(\sqrt{\rho}\,dW_t + \sqrt{1-\rho}\,dZ_t^i\Big). \tag{12}$$

In STACR securitizations, the underlying reference mortgage assets are fixed-rate. However, the bonds issued through the synthetic securitization of these fixed-rate mortgages are floating-rate. I therefore model the underlying asset process and the tranches written on these assets as floating-rate instruments. I interpret the underlying assets in this synthetic securitization as a combination of fixed-rate instruments and interest rate swaps. The terminal promised amount of the floating rate loan balance (where F_0 is normalized to \$1) is given by:

$$F_T = F_0 \exp\left(\int_0^T r_s\,ds\right). \tag{13}$$

In the special case that the tranche spread $y = 0$, the terminal value of $Tranche_T^{a,d}$ following the stochastic rate path is given by:

$$Tranche_T^{a,d} = \exp\left(\int_0^T r_s\,ds\right)\left((d-a) + min[max[Loss_T + a, (a-d)], 0]\right). \tag{14}$$

The updated present value of the tranche at origination is given by taking the risk-neutral expectation after integrating over the stochastic rate path:

$$Tranche_0^{a,d} = \mathbb{E}^Q\left[\exp\left(-\int_0^T r_s\,ds\right)\,Tranche_T^{a,d}\right] \tag{15}$$

Because any tranche pays a floating rate, discounting back to time 0 under the stochastic short-rate process exactly offsets the bond's coupon. That is, in the absence of default, the rate path does not affect the investor's value of the tranche at origination.

From the perspective of the borrowers, the prepayment decision is driven by whether the PV of the remaining fixed-rate mortgage payments is greater than the cost of buying back the loan at its face value. To model the borrower's decision on the fixed rate leg of the mortgage, I find the fixed rate coupon, r_{fixed}, that solves the following equation at the time of origination:

$$F_0 = \mathbb{E}^Q\left[\exp\left(\int_0^T r_s\,ds\right)\right] F_0 \exp(r_{fixed} * T). \tag{16}$$

As before, default occurs if the asset value is below the promised face value of the loan at the terminal time T. However, I model the borrowers' decision to prepay by giving the borrower the option to buy back the mortgage at the promised fixed rate face value at any time t:[24]

$$F_t^{Fixed} = F_0 \exp(r_{fixed} * t). \tag{17}$$

The borrower's incentive to endogenously prepay will increase when rates decrease, which increases the NPV of the remaining mortgage payments. Intuitively, the borrower decides whether to repay by comparing the option of buying back the mortgage at the outstanding fixed rate balance, F_t to the market value of the remaining mortgage balance, M_t:

$$M_t^{fixed} = \mathbb{E}_t^Q \left[\exp\left(\int_t^T r_s \, ds \right) \right] F_0 \exp(r_{fixed} * T). \tag{18}$$

In the spirit of Chernov et al. (2018), I incorporate prepayment intensity as increasing in the call option to repurchase the mortgage at F_t.

$$x_t \equiv \max\left(M_t^{\text{fixed}} - F_t^{\text{fixed}}, \, 0\right) \tag{19}$$

This approach slightly differs from Chernov et al. (2018), which models prepayment incentives in the difference between the contract rate and the refinance rate. Using NPVs rather than rates has the advantage of directly incorporating burnout as the NPV of refinancing shrinks as the loan approaches its contractual maturity.[25] I then follow Chernov et al. (2018) and incorporate repayment intensities in a model affine in this incentive to prepay:

$$\lambda_t = \lambda_0 + \lambda_1 \, x_t \tag{20}$$

The term λ_0 represent the baseline refinancing rate for idiosyncratic reasons, such as moving

[24] Additionally, note that F^T, not F_T^{Fixed}, determines the terminal default condition. F^T is the promised value of the underlying assets from the perspective of investors holding bonds in the synthetic floating rate securitization. F_T^{Fixed} is the fixed rate balance (assuming no credit risk) from the perspective of the borrowers who have not purchased any interest rate swaps.

[25] I show that the results to incorporating a kink in the prepayment intensity function to model fixed cost associated with prepayment. Table A10 reports the estimation results when assuming a fixed 3% prepayment cost.

for employment-related reasons. The term λ_1 captures the sensitivity to the incentive to refinance and can be interpreted as capturing costs associated with refinancing. In terms of the estimation, I set $\lambda_0 = 0.07$, which is near the average implied turnover rate in Chernov et al. (2018) and corresponds to the conditional prepayment rate during rate hike periods.[26] I add λ_1 as an additional parameter to estimate, and another tranche price, the second most junior sold tranche, as an additional moment in the model to match. At time t, an outstanding loan then has a probability p_t^{refi} of being prepaid.[27]

$$p_t^{\text{refi}} = 1 - \exp(-\lambda_t \, dt) \,. \tag{21}$$

The above approach captures prepayment incentives that exist in the absence of default risk. In for a loan to prepay, I additionally require that it is "current." Although loans may only default at the terminal time T, I define a loan as current if the time $t < T$ asset value exceeds the current promised face value at the same time, $A_t > F_t$. In other words, the borrower cannot exercise the option to buy back the face value of the loan if the asset value is not larger than the face value. This condition captures that, in practice, distressed borrowers may not be able to refinance even if rates are cut.

Because the loans in the model do not amortize, I model the mortgage scheduled principal payments by assuming that in each period t, a fraction $f_t^{r_{fixed}}$ of the loans in the pool are prepaid on "current" mortages, where $f_t^{r_{fixed}}$ is the amount of principal scheduled to be repaid at time t on \$1 of mortgage with interest rate r_{fixed} that fully amortizes over 30 years.

Tranche Prepayment

Next, I update the model to incorporate how CRT tranches are differentially affected by the prepayment speed of the underlying loan pool. The baseline model described above assumes that cash flows are paid sequentially in order of most senior to most junior tranches. In practice, if the loan pool is performing well, the CRT securities will allocate repaid

[26]The implied rather than empirical turnover rate is more appropriate for the model, because it is based on risk-neutral probabilities.

[27]When a loan "prepays" in the model, I set the loan value at the time of prepayment equal to the repaid promised face value $L_t^i = F_t^1$. In the model, F_t^1 then grows at the stochastic short rate until time T. Because all payoffs at time T are discounted back to the initial time zero using the same rate path, this is equivalent to taking the PV of the loan at the time of its prepayment.

principal pro rata between the supersenior and subordinate tranches.[28] If the loan pool is not performing well, the repaid principal is allocated sequentially to the supersenior and then the subordinate tranches.

In practice, CRT securities rely primarily on a set of thresholds to determine how repaid principal is allocated between tranches. In particular, pro rata repayment is only allowed if the supersenior tranche has a sufficient amount of "minimum credit enhancement" from the subordinate tranches. This means that the outstanding balance of the subordinate tranches, as a fraction of the outstanding loan balance, must exceed a given percentage that is just larger than the total size of the subordinate tranches.[29] The loan and subordinate tranche balances are affected by both prepayments and defaults, which result in writing down the balances.

To account for these features in the model, I assume that the principal is paid pro rata between supersenior and subordinate tranches only when this threshold is satisfied. Let $L_{t,out}$ denote the amount of nonprepaid loans outstanding at time t and $T^{a,d}_{t,out}$ denote the balance outstanding of a tranche that attaches at a and detaches at d at time t. To adjust for "write-downs" from delinquent loans on the tranches, I define $L_{t,adj} = \frac{L_{t,out}}{I_{out}} \sum_{i \in I_{out}} \min(A_{i,t}, F_t)$ and $T^{a,d}_{t,adj} = T^{a,d}_{t,out} - \min((L_{t,adj} - L_{t,out}), -1 \times T^{a,d}_{t,out})$. In words, $L_{t,adj}$ measures the current value of the remaining loan pool if underwater loans were to default immediately, and $T^{a,d}_{t,adj}$ represents the tranche balance after allocating these interim unrealized losses to the subordinate tranches.

In the model, I then define the credit enhancement ratio trigger as $T^{0,d_{max}}_{t,adj} / L_{t,adj} > d_{max}$ where d_{max} is the detachment point of the most senior subordinate tranche and $T^{0,d_{max}}_{t,adj}$ denotes the total adjusted outstanding balance of the subordinate tranches.

After initializing $T^{0,d_{max}}_{0,out} = d_{max}$, the law of motion of the subordinate tranche balances

[28] Of the pro rata payments to the subordinate tranches, the principal is allocated sequentially to the most senior subordinate tranches before the junior subordinate tranches receive principal.

[29] Additionally, to switch from sequential to pro rata to payments, the loan pool must pass a cumulative net loss (CNL) test. In particular, the principal repayment switches to sequential payments if the "cumulative net loss ratio" in a given year exceeds $min(.1\% * t, 1.3\%)$ where t is years. This cumulative net loss ratio test is near uniform across Freddie Mac STACR deals. Writing the CNL ratio as $(F^2_t - L_t)/F^2_t$, I show in Table A9 in the appendix that the estimation results are robust to imposing this constraint in the model.

can therefore be given by:

$$T^{0,d_{max}}_{t,out} = \begin{cases} T^{0,d_{max}}_{t-1,out} - (L_{t-1,out} - L_{t,out}), & \text{if } (1 - L_{t-1}) - (d_{max} - T^{0,d_{max}}_{t-1,out}) < (1 - d_{max}) \\ T^{0,d_{max}}_{t-1,out} - d_{max} * (L_{t-1,out} - L_{t,out}), & \text{if } T^{0,d_{max}}_{t,adj} / L_{t,adj} > d_{max} \\ T^{0,d_{max}}_{t-1,out}, & \text{otherwise} \end{cases} \tag{22}$$

In words, all principal is allocated to the subordinate tranches if the supersenior tranche of initial size $(1 - d_{max})$ has been entirely repaid. If the supersenior tranche is outstanding and the credit enhancement thresholds are satisfied, then the subordinate tranches are allocated principal pro rata. Otherwise, the subordinate tranches receive no principal.

Within the subordinate tranches, all principal is allocated sequentially. Therefore, the outstanding balance of a specific tranche that attaches at a and detaches at d can be written as:

$$T^{a,d}_{t,out} = min(max(T^{0,d_{max}}_{t,out} - a, 0), d - a) \tag{23}$$

A tranche pays an interest rate y on its balance outstanding $T^{a,d}_{t,out}$, and I model prepayment by assuming that any repaid balance continues to pay the risk-free rate $r \leq y$. Letting y^{adj} denote the prepayment adjusted coupon, the terminal value of a tranche that reflects prepayment is therefore:

$$Tranche^{a,d}_{T} = (d - a) * \exp\left(\int_t^T r_s \, ds\right) * (1 + min[max[Loss_T + a, -1 * T^{a,d}_{T,out}], 0]). \tag{24}$$

Intuitively, if the tranche is prepaid entirely, the value of the tranche is equal to its promised value under the realized short rate path. If there is a nonzero balance outstanding at the end of the final period, the maximum the tranche can lose is proportional to this outstanding balance.[30] Although there may be pro rata prepayment between the supersenior and subordinate tranches, all payments within the subordinate class are sequential, meaning that there is a amount of credit enhancement as long as some of the tranche balance is outstanding.

[30] Because delinquent loans cannot prepay, they will survive until the terminal period T without returning any principal.

Endogenous Prepayment Implmentation

To estimate the version of the model with prepayment, I discretize the Brownian shocks in Equation (7) into 30 one-year periods over the life of a 30-year mortgage. I calibrate the Vasiciek parameters to match an AR(1) process on 3 month treasury both rates over 1995 to 2026. The calibration results are detailed in Table A11. In each of the 30-year periods, I iterate the asset values using Equation (7), calculate the prepayment intensity and refinance a fraction of outstanding loans, apply scheduled principal payments, check whether the credit enhancement trigger is satisfied, and compute the updated subordinate tranche balances. Finally, I obtain the terminal value of the tranches and the loan portfolio, of which I take expectations and discount back to the initial time under the stochastic rate process. As in the baseline version of the model, for tractability, I set the tranche interest rate spreads equal to zero. Doing so treats model estimation as matching the market value of expected losses for each tranche, analogous to pricing a credit derivative that pays the floating risk-free rate and incurs losses.

3.2.3 Reinsurance Valuation Results

Table 5 presents summary statistics on the STACR tranches that are used in the valuation exercise. The table reports the mean tranche size, attachment point, detachment point, interest rate spread, weighted average life, market price, and loss ratio for the tranches. On average, each of the subordinate tranches comprises about 1% of the total deal size. The senior tranches have a 3.2% attachment point on average, which indicates that they have a buffer of initial subordination before they incur any losses. In contrast, the junior tranches have little or no initial subordination. As a result, they carry higher interest rate spreads. In terms of weighted average lives (computed in the absence of default), the junior sold tranche has significantly higher lives because, although they are expected to take losses first, they are repaid last. The most junior sold tranche has a weighted average life of 8.9 years, compared to the most senior sold tranche, which only has a weighted average life of 1.2 years.

For each tranche, I calculate the expected loss ratio as the market value of expected losses per dollar invested in that tranche. The market value of expected losses is computed by deducting the PV of the coupon payments in the absence of default from the observed market price. On average, the junior tranche has an expected loss ratio of 68%, whereas the most senior sold tranche has a smaller loss ratio of just 1.4%. The market values of expected losses for each tranche are the key empirical moments matched in the model estimation. The key unknown estimated by the model is the market value of expected losses for the supersenior tranche that is retained by Freddie Mac. Intuitively, because the supersenior tranche has a larger amount of initial subordination than the senior tranche, one would expect a lower loss ratio for the supersenior tranche; however, the magnitude of these losses is an important empirical question. The sum of the tranche sizes times the loss ratios determines the total market value of expected losses on the loan pool.

Table 6 presents the results from the structural estimation. Panel A contains the results on the approach when assuming that the supersenior tranche is default-free and that any nontraded superjunior tranches experience a 100% loss. The average actual guarantee fee that Freddie Mac charges at the time when these STACR transactions are issued is 57 bps. Using the approach above, I find that the market value of expected losses implied a guarantee fee of only 24.5 bps, which suggests that Freddie Mac charges roughly twice what market participants require to hold the same risk.

Panel B presents the estimates from the baseline structural default risk model. I find that the estimated model parameters, the market value of collateral, the volatility of the collateral, and the loan pool correlation are on average \$1.25, 5%, and 0.16 across the STACR transactions, respectively.[31] Unlike the previous case, these estimates explicitly account for the expected losses on nontraded tranches by matching the prices of the traded tranches. The model finds that a market participant requires 24 bps annually to compensate for the market value of expected losses from the loan pool.[32] Even with this more conservative estimate, it implies that the guarantee rates that Freddie Mac charges are still roughly double what

[31]The estimated ρ parameter of 0.16 corresponds closely to the asset correlation parameter for 'retail residential mortgage exposures' of 0.15 used in the Basel Capital framework (See: https://www.bis.org/baselframework/BaselFramework.pdf). The value of the collateral parameter implies an average market LTV of 0.80 for the loans.

[32]Compared to the previous estimate, this version explicitly takes into account the tail risk of the loans, leading to larger expected losses. However, this version also does not impose that the superjunior tranches incur 100% losses, which reduces the expected losses compared to the previous version. The net effect is a larger market rate guarantee fee. Table A8 in the Appendix reports results for the subsample of STACR deals without retained superjunior tranches.

a market participant would charge to hold a security of identical risk. Figure 4 plots the actual guarantee fees versus the market rate guarantee fees over the sample period of STACR transactions. Comparing these estimates to the previous cash flow valuation exercise in Table 4 implies very similar estimates. Annualizing the post-crisis PV(GSE Guarantee) of $0.012 from the GPME with a WAL of 4.2 indicates that Freddie Mac overcharges by 29 bps.

Panel C presents the results from the endogenous prepayment version of the model. The average estimated parameters are similar to those in the previous version of the model, with an annualized volatility of assets of 5% and an asset value of 1.12, which implies a market LTV of 89%. The correlation of the asset pool characterized by ρ is also higher at 0.30. The new estimated parameter λ_1 determines the sensitivity of borrowers to the call option value of early prepayment. The average estimated λ_1 across the deals is 19.45 and the corresponding weighted average life of the loans in the model is 5.3 years, which is close to the average realized WAL of 4.2 of the mortgages over the sample period. The estimated market rate guarantee fees are higher using the prepayment version of the model at 26.4 bps. Intuitively, because this version allows the sold tranches to be prepaid before the supersenior tranche is exhausted. As a result, there are more states in which the supersenior tranche becomes impaired. The resulting tail risk amounts roughly to an additional 3 bps in the annualized cost of insuring the loans.

Taken together, these findings further reinforce the interpretation that the GSEs charge an above-market price for their credit risk insurance in the post-GFC period and illustrate that actual market participants are willing to bear this risk and even pay a lower price for it.

3.3 Bank GSE Selling Behavior

If Freddie Mac overcharges for mortgage guarantees relative to its market price, do banks reduce their use of GSEs because of these increased costs? An above-market price for GSEs to insure the credit risk implies that banks would be relatively better off retaining the mortgages on their balance sheet or privately securitizing them using market-based funding. Consistent with this idea, in Figure 5, I document that banks reduce their loan sales to GSEs by 10pp following the increase in pricing. However, bank originators continue to sell over 40% of their loans to GSEs despite the above-market price, and their distribution of newly originated loans still exhibits bunching around the conforming loan limit (Figure 6), suggesting that there is still an advantage to using GSEs.One potential economic force that explains these patterns is the presence of balance sheet constraints, which would make lenders willing to continue securitizing through GSEs despite the above-market rate.

To empirically test how balance sheet constraints affect bank selling decisions, I study lenders' decisions to sell conforming eligible mortgages to GSEs.[33] In particular, I examine how lender balance sheet constraints affect their selling behavior of conforming eligible loans in response to increased GSE guarantee pricing. To this end, I examine two dimensions of balance sheet constraints. First, I sort lenders into banks and nonbanks. Relative to banks, non-banks have relatively limited options to retain loans on their balance sheets and difficulty relying on illiquid jumbo securitization markets (e.g., see Buchak et al. (2018a) Fuster, Hizmo, Lambie-Hanson, Vickery, and Willen (2021)). When GSEs increase the price of insuring mortgages, I therefore expect that nonbanks will be relatively more likely to continue to sell to GSEs.

Second, I examine variation in balance sheet constraints within bank lenders. Following Buchak et al. (2018a), I expect that banks with lower tier 1 capital ratios will have relatively higher shadow costs of balance sheet retention. Likewise, I expect smaller banks and banks with lower amounts of deposit funding to have relatively higher costs of financing loans on their balance sheets. I measure these characteristics using their bank holding company data from FRY-9C and merge this data to HMDA [34]

Table 7 presents the results. The table shows a clear pattern that when guarantee fees rise, more constrained lenders are more likely to continue selling conforming eligible loans to GSEs. Following a 10 bps increase in guarantee fees, nonbank lenders are 10 pp more likely to sell their GSEs compared to banks. The 10 pp decline in probability represents an approximate 20% decline relative to the unconditional probability of lenders selling loans to the GSEs.

Among banks, those with a 1 standard deviation higher tier 1 capital ratio are 1 pp less

[33]When a bank uses one of the GSEs for mortgage guarantees, typically, banks swap their credit-risky mortgages for insured MBS after paying a guarantee fee to the GSE. I refer to this transaction as a mortgage sale to GSEs because the GSE acquires the underlying mortgages and bears any associated credit risk.

[34]Bank characteristics are measured in 2012 before the rate hike in guarantee fees as shown in Figure 3.

likely to sell a given loan to GSEs following a 10 bps hike in g-fees. Likewise, larger banks and banks with more deposit funding are also less likely to make loans to GSEs following a hike in guarantee fees. These results support the prediction that balance sheet constraints are relevant at the margins in terms of whether lenders continue to use GSEs even when the costs are above market rates.

Another directly testable implication is that if GSEs reduce their subsidies/increase their guarantee pricing, mortgages should bunch less around the conforming limit. I test this implication in Figure 6, which plots the distribution of loans around the conforming loan limit before (2009-2013) and after (2015-2017) the conforming-nonconforming loan spread inversion in 2014. The figure shows strong bunching behavior at the conforming loan limit, indicating that there is something valuable that borrowers/lenders find about selling mortgages to the GSEs. After the inversion of the nonconforming spread, bunching at the limit decreases from 15% of the distribution to 12%, consistent with a lower subsidy provided. Surprisingly, the post-inversion period still exhibits significant bunching despite the higher guarantee pricing and the lower fraction of loan sales to GSES.

3.4 Jumbo - Conforming Mortgage Spread

To supplement the previous analysis, I also present reduced-form evidence inconsistent with the GSEs providing a subsidy during the post-GFC period. In particular, I examine loan pricing around the conforming loan limit, which is a an important institutional feature in GSE-based mortgage securitization. Each year, Fannie Mae and Freddie Mac set a maximum loan limit, which may vary by county, on the size of the mortgages they are allowed to purchase and insure. If GSE securitization offers a subsidy, then all else equal, nonconforming loans just above the loan limit will be more expensive and require higher loan rates. In contrast, if this subsidy has been eliminated by increased guarantee fees in the post-GFC period, the spread to compress toward zero or even become negative.

To test the prediction, I examine the relative pricing of conforming and nonconforming mortgages in the post-GFC period using the most recent HMDA data covering mortgages in 2018 and 2019.[35] Importantly, unlike the older version of HMDA data, the new version

[35] In this baseline analysis, I exclude the COVID-19 crisis period in 2020-2022. Figure A4 in the Appendix

contains information on mortgage interest rates, which are needed to estimate the spread between jumbo and conforming mortgages. Traditionally, research has found that jumbo loans have higher interest rates than conforming mortgages, suggesting that GSEs offer a subsidy to borrowers (e.g., Passmore et al. (2005)). After the hike in Fannie and Freddie's insurance premiums, as shown in Figure 3, it is not clear that this spread should remain positive in the post-GFC period.

To estimate the spread between nonconforming and conforming mortgages, I begin by implementing a regression discontinuity design around the conforming loan limit, above which GSEs cannot insure/securitize mortgages (DeFusco and Paciorek, 2017; Fisher et al., 2021). I use a bandwidth of loan amounts $50,000 above and below the conforming limit in all specifications.[36]

Figure 7 plots the loan interest rates around each side of the conforming loan limit cutoff in the years 2018 and 2019. The figure shows a sharp decline in rates for mortgages with loan sizes just on the other side of the conforming loan limit in the post-GFC period. Table 8 tabulates these results, finding that jumbo loans are cheaper by 10 to 20 bps points on average, even when controlling for differences in loan-to-value, debt-to-income, closing costs, year fixed effects, census tract fixed effects, and lender fixed effects. This finding that jumbo loans are cheaper than conforming loans in the post-GFC period contradicts the notion of a GSE subsidy and corroborates the earlier findings that their guarantee fees are overpriced.

In Figure 9, I use the same procedure to estimate a time series of the nonconforming-conforming spread from 2009 to 2018 using the survey MIRS data from FHFA. I also plot the time series of the NPV of the Freddie Mac cash flows using the RAP methodology. The figure shows a strong inverse relationship between the valuation of the guarantee cash flows and the jumbo-conforming spread. Prior to 2014, conforming mortgages were more expensive than nonconforming mortgages. This relationship inverted in 2014, around the same time that

documents the nonconforming spread over 2009 - 2022 by combining estimates from both the MIRS and HMDA datasets. I also include the time series of spread separately for banks and nonbanks when the data is available, beginning in 2018. The spread becomes zero again in 2020/2021, consistent with lender financial constraints due to the stress from the COVID pandemic, making it relatively more difficult to finance loans on the balance sheet, but it becomes negative again in 2022.

[36] This cutoff corresponds closely to the optimal bandwidths estimated by using the methods of Calonico, Cattaneo, and Titiunik (2014). I also use a simple linear polynomial on both sides of the cutoff, which is the optimal polynomial estimated by the methods in Calonico et al. (2014).

GSEs increased their premiums and the valuation of the guarantees increased (see Figure 3). The guarantee values and spread also shrank together in 2016 and 2017, when GSEs slightly reduced their premiums. This evidence further suggests that the pricing and valuation of GSE mortgage guarantees are related to the relative pricing of conforming and nonconforming loans.

A caveat to this analysis is that an above-market guarantee fee alone should drive the spread to zero, rather than below it. This is because banks also have the option of balance sheet retention below the conforming loan limit. If GSE fees exceed the market price of risk, the bank can simply choose to hold a conforming loan on its balance sheet. Therefore, even if balance sheet financing is cheaper than GSE securitization, there should be no difference in marginal cost or rates across the threshold since both options are available for conforming loans. The fact that the spread becomes strictly negative is likely driven by a selection effect, where banks screen jumbo borrowers more rigorously because those loans must be retained on the balance sheet. Despite this potential selection effect, a negative spread remains inconsistent with a GSE subsidy.

To further investigate how this spread is driven by differences in balance sheet costs of retention compared to GSE insurance pricing, I exploit a feature of the HMDA dataset, which separately identifies bank and non-bank originators in the micro-data. Therefore, I can separately estimate the nonconforming-conforming loan spread for banks and non-banks. If banks can finance loans closer to market-risk rates via balance sheet financing, then the nonconforming spread should be lower for banks relative to non-banks originators who face greater balance sheet constraints.[37] Although the selection effect should be similar across lender types, the balance sheet costs of funding these loans on-balance sheet should differ across these lender types.

Panel A of Table 9 presents the results. There is a negative jumbo-conforming spread of around 18-28 bps for the subsample of banks. This is further consistent with GSE insurance pricing exceeding the market price of risk, and that banks can access that market price by funding the loans on the balance sheet. Further, the gap in the jumbo-conforming spread for

[37] In the post-GFC period the private jumbo securitization market was fairly illiquid meaning that balance sheet retention rather than private securitization was the more prominent alternative at the time (e.g, see Buchak et al. (2018a), Fuster et al. (2021))

non-bank originators is smaller at around 10 bps.[38] This finding is consistent with nonbanks facing relatively stronger balance sheet constraints for retaining loans (Buchak et al., 2018a).

A concern with this analysis so far is that loan size and, therefore, whether a borrower takes out a jumbo or conforming loan is a choice determined by the borrower. A regression discontinuity design using the loan amount as the running variable is potentially problematic because of the lack of a smooth distribution around the cutoff. To address this concern, I follow Kaufman (2014) and use an alternative RDD approach to instrument for whether or not a loan is jumbo. In particular, these papers exploit the fact that borrowers cannot control their home appraisal values, and whether the value comes in at or below an 80% LTV of the desired loan amount determines if a bank is willing to hold the loan on the balance sheet as a jumbo loan. To implement an RDD design with this alternative cutoff, they define the 'appraisal limit' as the conforming loan limit divided by 0.80. In this setting, the running variable is the home's appraisal value minus the appraisal limit.[39] If a home appraisal value comes in at just below the appraisal limit, the borrower can obtain a conforming loan with less than a 20% down payment, but to qualify for a balance sheet loan, they would have to take a smaller loan. Just above the appraisal limit, a borrower can get a jumbo mortgage with exactly a 20% down payment and even reduce their desired loan amount. However, above the appraisal limit, the borrower must put down more than 20% in order to qualify for a conforming mortgage. For this reason, it is likely that home appraisal values above the appraisal limit are more likely to be jumbo loans.

Figure 8 plots the probability that a loan is jumbo and the interest rate spread around the appraisal limit. In this test, I start by only examining loans originated by banks, because they have balance sheet capacity to retain jumbo loans, unlike nonbanks (e.g., see Buchak et al. (2018a)). Panel A plots the first stage of whether the appraisal limit cutoff is empirically relevant for whether a bank loan is jumbo or conforming in the post-GFC period. The figure shows a sharp and discontinuous increase in the probability that a loan is jumbo above the appraisal limit, in line with the first stage found by Kaufman (2014) in the pre-GFC period.

[38]Figure A3 in the Appendix plots the rates across the conforming loan limit for both types of lenders.

[39]Table A2 in the Appendix plots the kernel density for the loan amount around the conforming loan limit versus the kernel density of the loan appraisal value around the appraisal limit. The figure shows that although the distribution around the conforming loan limit exhibits bunching, the distribution around the appraisal limit does not.

However, unlike the pre-crisis, Panel B shows that the interest rates are discontinuously lower above the appraisal limit. In Table 9, Panel B tabulates this reduced form result as well as the 2SLS estimate, which shows that instrumented bank jumbo loans have approximately 10 bps lower interest rate spreads. The magnitude of this estimate is similar to the previous conforming loan limit RDD approach and reaffirms the interpretation that the guarantee fee overpricing affects the cost of mortgages.

In contrast with banks, Table 9 shows that nonbanks originators exhibit a positive jumbo-conforming spread when using the 2SLS instrumented value of jumbo.[40] This finding reinforces the view that even if GSEs charge an above-market rate for credit risk insurance, the limited balance sheet capacity of nonbanks prevents them from accessing any cheaper type of financing.

4 Conclusion

This paper investigates whether government-sponsored enterprises (GSEs) subsidize the credit risk of conventional residential mortgages. Using a novel dataset of Freddie Mac's guarantee cash flows from 1999 to 2018 and comparing them against publicly traded benchmarks, I uncover several findings. First, I show that GSEs provide a credit risk subsidy during the pre-GFC period on the order of magnitude of 20 bps annually. Second, I find that GSEs do not provide a subsidy after the GFC and instead earn positively and economically significant profits on their guarantees, consistent with higher guarantee fees and stricter post-crisis underwriting standards. Third, although banks do reduce their reliance on GSEs in response to the above-market pricing of guarantees, they continue to sell a substantial share of their loans to GSEs. At the margin, more balance sheet-constrained lenders rely more on GSE securitization as GSE insurance prices increase. These results challenge the view that lenders use GSEs primarily to access subsidized pricing and instead imply that

[40] A related concern is that banks may offer lower spreads on mortgages due to cross-selling incentives. To address this, in Table A7 I drop the five largest banks in the sample, as larger banks are generally thought to have stronger cross-selling incentives. Moreover, for this concern to affect the estimates, cross-selling incentives would need to vary discontinuously around the conforming loan limit, which seems unlikely given that banks retain the ability to cross-sell regardless of whether they hold a mortgage on their balance sheet or sell it to the GSEs.

balance sheet costs and other costs explain why lenders use GSEs despite their above-market rates in the post-crisis period.

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Figure 2: Average Guarantee Net Cash Flow by Horizon

Figure 2 plots the average net cash flow distribution of the GSE guarantees by years since the loan was originated.

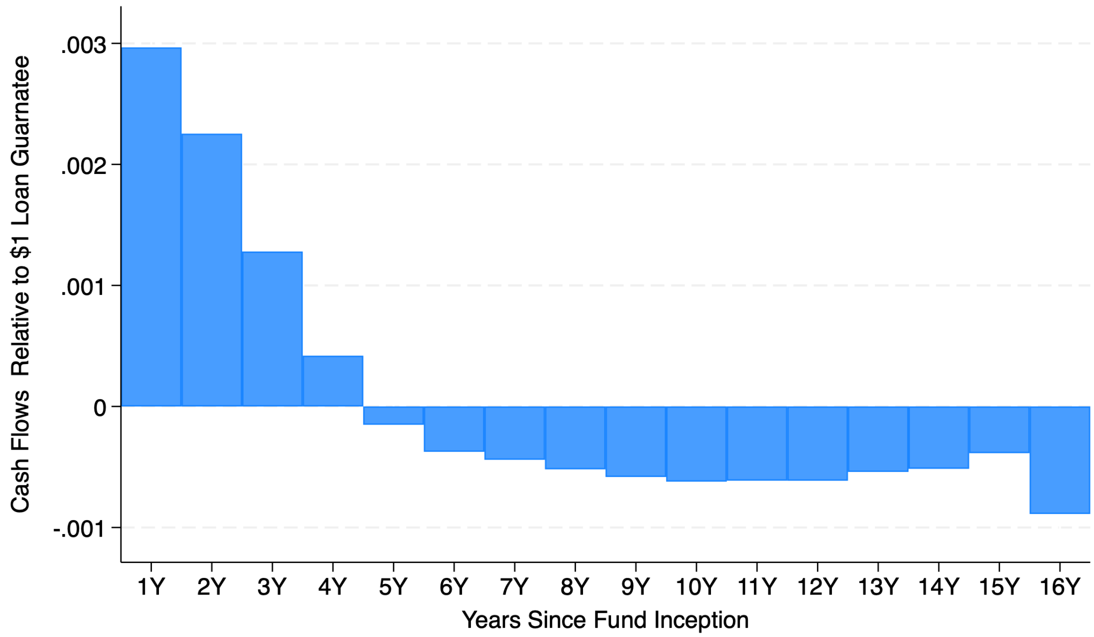


Figure 3: Freddie Mac Guarantee Fees over Time

Figure 3 plots Freddie Mac's average effective guarantee fees on new mortgage originations over time in basis points.

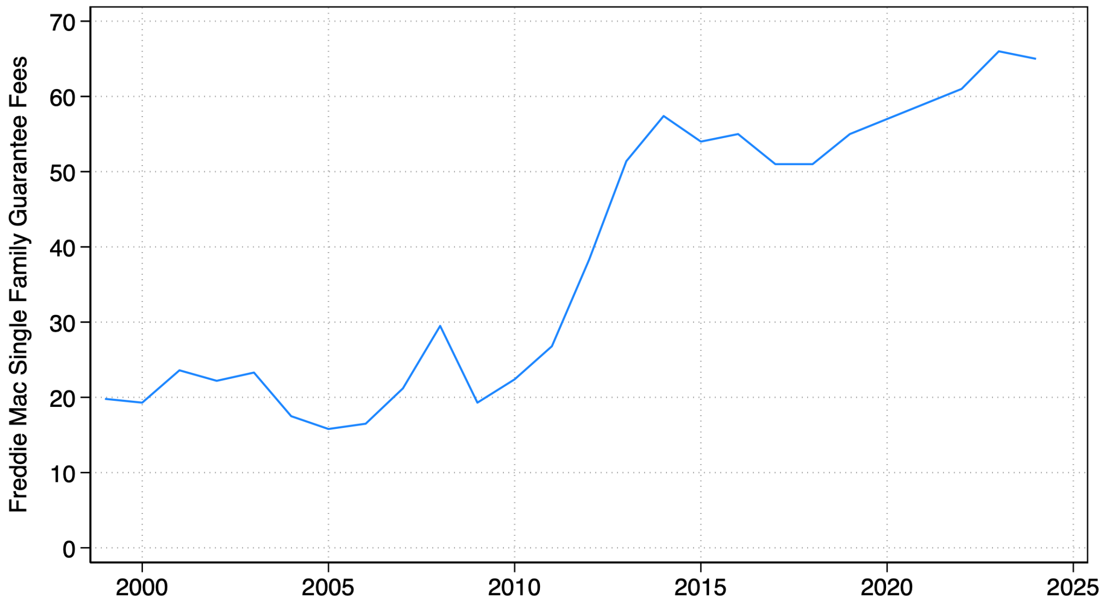


Figure 4: Actual G-fees and Market Implied G-fees

Figure 4 reports the market rate guarantee fees from estimating the Nagel and Purnanandam (2020) model to match the market prices of the junior subordinate and senior subordinate Freddie Mac STACR tranches. The figure reports time series averages of Freddie Mac's actual g-fees in a given year that a STACR deal was originated versus the market rate guarantee fees. All estimates are reported in basis points.

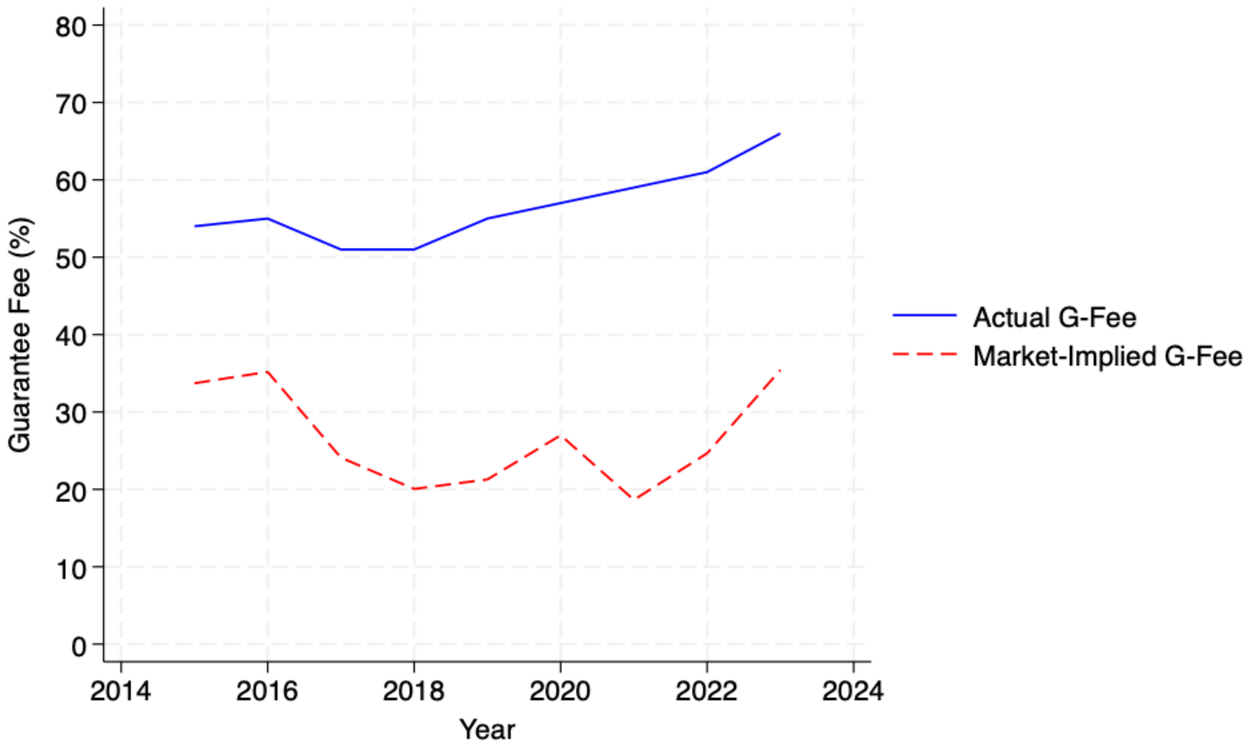


Figure 5: Bank Use of GSE Securitization Over Time

Figure 5 plots the total fraction of bank originated loans sold and securitized to the GSEs over 2008 to 2017 verus the average gurantee fees over the same time horizon. The fraction of bank loans sold is calculated using HMDA data.

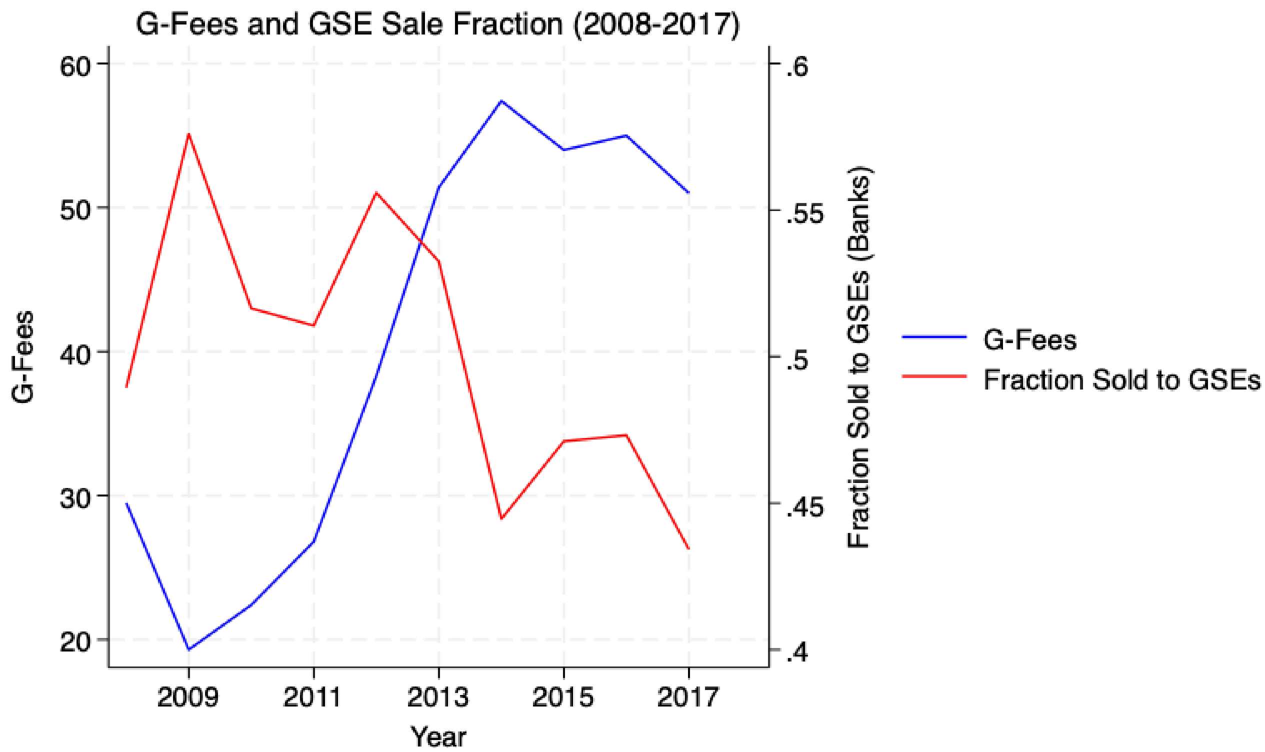


Figure 6: GSE Sold and Non-Sold Bunching

This histogram plots the distribution of loan amounts around the conforming loan limit for loans before (2009 - 2013) and after (2015 - 2017) the 2014 guarantee fee hike using the 2009-2017 HMDA dataset.

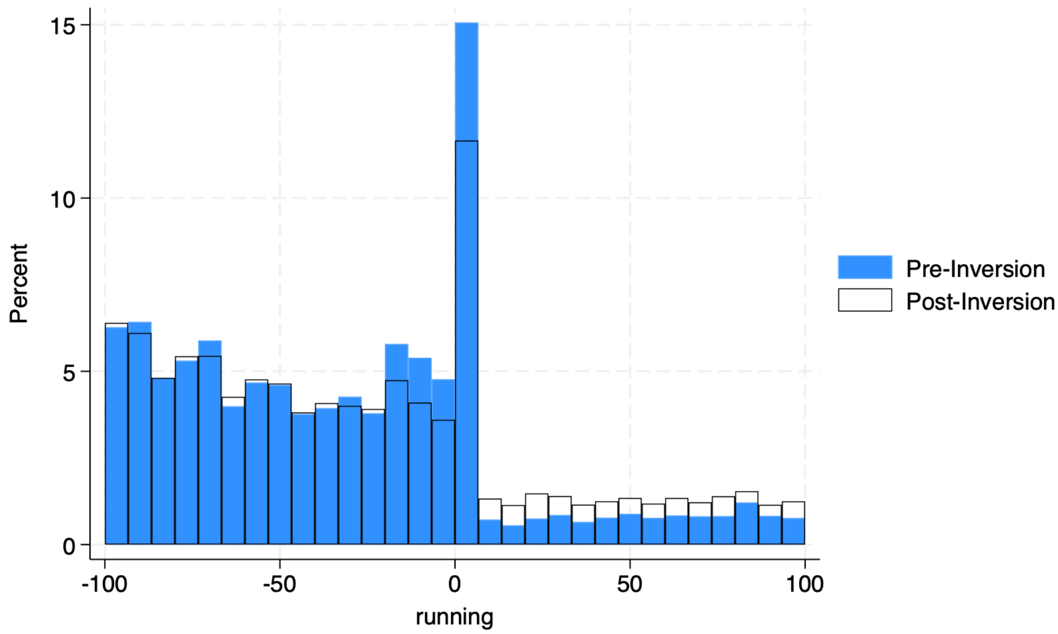


Figure 7: Jumbo-Conforming Loan Spread

Figure 7 plots the discontinuity in the mortgage interest rates around the conforming loan limit using 2018-2019 HMDA data.

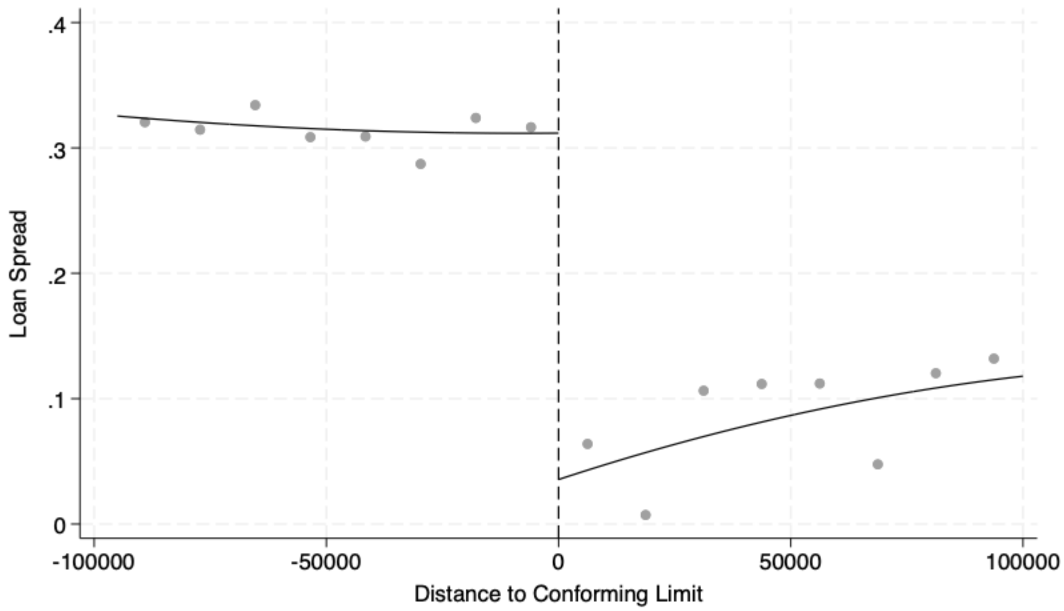
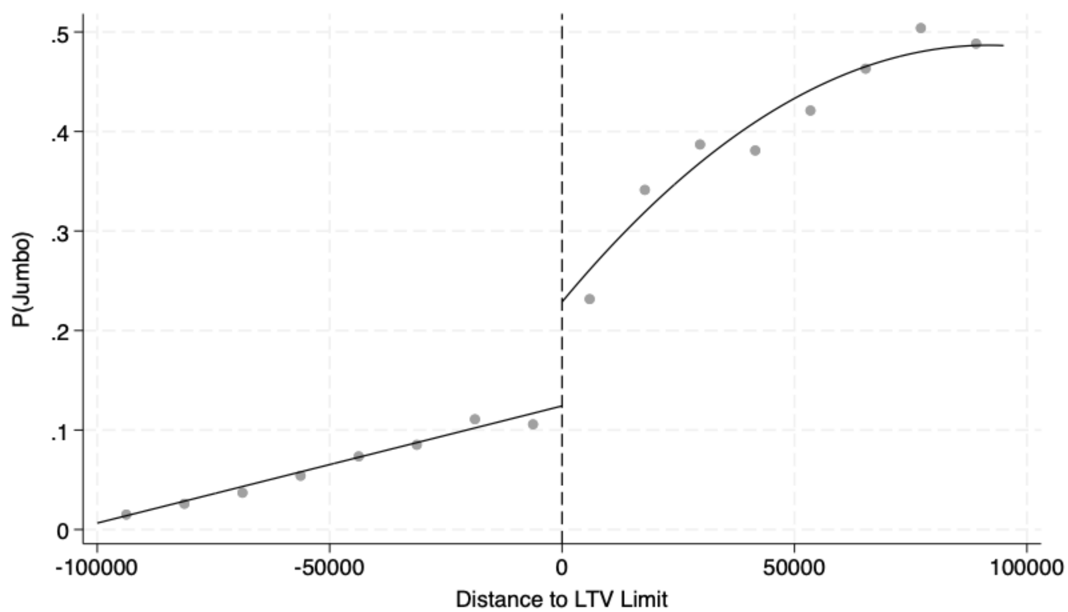


Figure 8: Instrumented RDD: Jumbo-Conforming Loan Spread

Figure 8 plots the conforming-nonconforming spread for bank-originated mortgages using a regression discontinuity design following Kaufman (2014) using the 80% LTV cutoff as an instrument for whether a loan is nonconforming/jumbo. The x-axis running variable is the home appraisal value minus the conforming loan limit divided by 0.80. Panel A plots the probability that a loan is jumbo around the appraisal LTV cutoff, which corresponds to the first stage of the IV regression.. Panel B plots the mortgage interest rate spread around the appraisal LTV cutoff, which corresponds to the reduced form of the IV regression.

(a) Panel A: First Stage



(b) Panel B: Second Stage

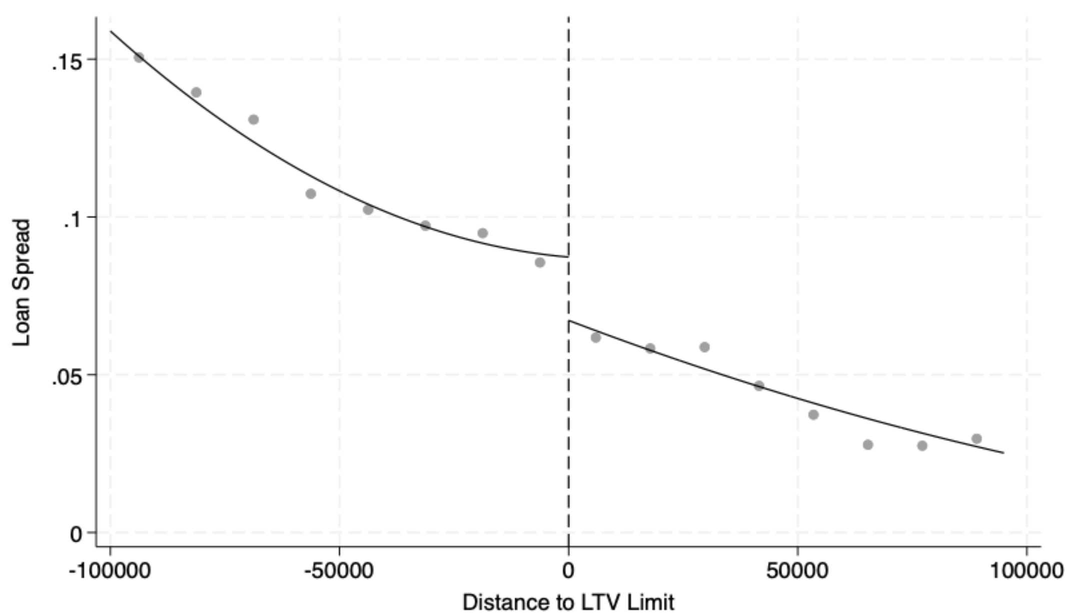


Figure 9: Nonconforming Spread and PV(GSE Guarantees)

This figure plots the time series of the valuation of the guarantee cash flows using RAP for discounting versus the time series of the estimated jumbo-conforming loan spread from 2009 to 2018.

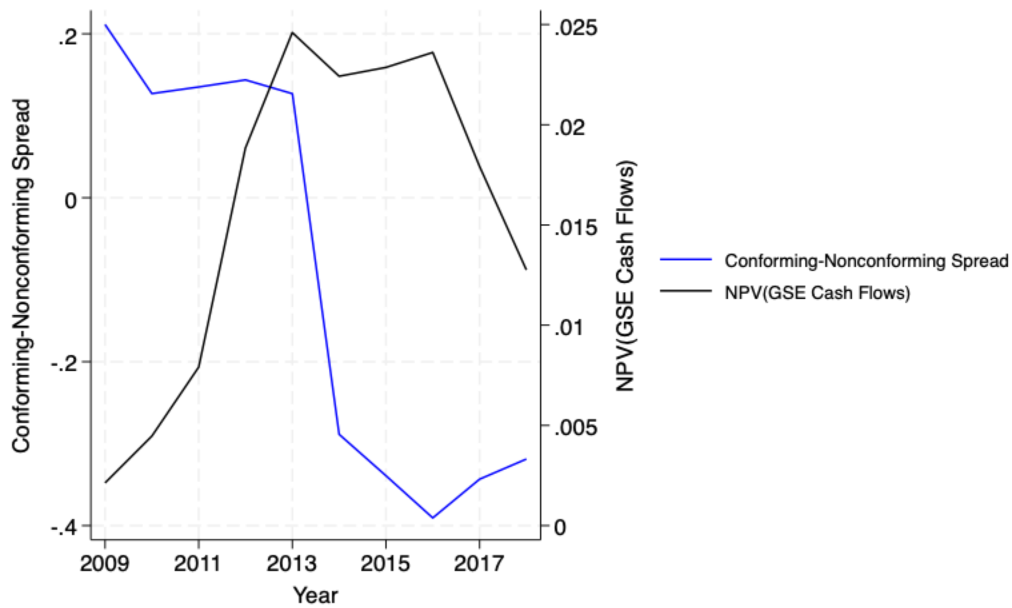


Table 1: Cash Flow Summary Statistics

Table 1 reports summary statistics for the loan guarantee cash flows. 'Weighted Average Life' is the length of years of the average outstanding principal balance of the loans that Fannie insures. 'Total Cash Back' is the raw amount of cash flows that Freddie Mac received from insuring loans that were originated in a given quarter. 'Guarantee Fee' is the average guarantee fee on new mortgage originations in a given quarter. 'Risk-Free Dollar PV' is the present value in dollar terms ($ millions) of the GSE guarantees computed using the term structure of risk-free rates. 'Risk-Free PV' is the present value per $1 of mortgage guaranteed.

	Mean	SD	Min	P25	P50	P75	Max	N
Total Loan Principal Guaranteed ($ Billions)	63.05	28.70	17.94	47.21	58.18	72.50	171.48	80
Weighted Average Life	4.18	1.08	1.84	3.58	4.37	4.89	6.19	80
Total Cash Back ($ Billions)	0.13	1.47	-4.88	0.01	0.40	1.00	2.62	80
Guarantee Fee (bps)	31.77	15.03	15.80	19.55	23.45	51.00	57.40	80
Risk-Free PV	0.004	0.02	-0.050	0.002	0.006	0.018	0.029	80
Risk-Free Dollar PV	263	1154.65	-3377	49	408	963	2505	80

Table 2: Value of GSE Guarantees: GPME

Table 2 estimates the value of the GSE guarantee cash flows using GPME. Panel A presents equal-weighted results, and Panel B presents the value-weighted results using the principal amount of the loan guaranteed as a weight. Columns (1)-(3) estimate the specification using different risk factors, and column (4) estimates an SDF using all three risk factors. The estimated SDF parameters are presented below the table.

Panel A: EW

	PV			
	(1) Stocks	(2) REITs	(3) MREITs	(4) All
PV(GSE Guarantee)	0.001	-0.001	-0.001	-0.000
	(0.002)	(0.003)	(0.003)	(0.003)

Panel B: VW

	PV			
	(1) Stocks	(2) REITs	(3) MREITs	(4) All
PV(GSE Guarantee)	0.000	-0.001	-0.001	-0.000
	(0.002)	(0.003)	(0.003)	(0.002)
$b1$	0.03	0.03	0.00	0.03
$b2$	2.52	1.98	1.14	0.42
$b3$				0.05
$b4$				2.19

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: Value of GSE Guarantees: RAP

Table 3 reports the risk loadings and corresponding guarantee risk-adjusted valuation from the risk-adjusted profit methodology. Panel A reports the risk loadings for the baseline specification that includes the a_h horizon intercepts for ZCB bonds, Stock (CRSP VW stock returns), MREIT (Nonagency MREIT benchmark returns), and REIT (Nareit REIT benchmark returns). Panel B reports both the total risk-adjusted valuation. Columns (1)-(2) are equal-weighted estimates, and Columns (3)-(4) are value-weighted estimates. The reported risk loadings correspond to the point estimates in Columns (2) and (4) that include all the benchmark returns. Columns (1) and (3) only include the Treasury and stock market benchmarks. Standard errors are in parentheses and computed using a non-parametric block bootstrap procedure.

Panel A: Risk-Loadings

	ZCB	Stock	MREIT	REIT
	(1)	(2)	(3)	(4)
Horizon 1	0.0008***	0.0008***	0.0002	-0.0008***
	(0.0000)	(0.0003)	(0.0003)	(0.0003)
Horizon 2	0.0005***	0.0009***	0.0001	-0.0005**
	(0.0000)	(0.0001)	(0.0002)	(0.0002)
Horizon 3	0.0002**	0.0009***	0.0003	-0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Horizon 4	-0.0001	0.0009***	0.0005**	-0.0002
	(0.0001)	(0.0002)	(0.0003)	(0.0003)
Horizon 5	-0.0004***	0.0008***	0.0005*	0.0000
	(0.0001)	(0.0001)	(0.0003)	(0.0005)
Horizon 6	-0.0004***	0.0006***	0.0005*	0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.0004)
Horizon 7	-0.0004***	0.0005***	0.0004**	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Horizon 8	-0.0004***	0.0004***	0.0004**	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Horizon 9	-0.0003***	0.0001**	0.0004***	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Horizon 10	-0.0003***	0.0000	0.0004***	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Horizon 11	-0.0003***	0.0000	0.0004***	-0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Horizon 12	-0.0002***	-0.0000	0.0004***	-0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Horizon 13	-0.0002***	-0.0000	0.0003***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Horizon 14	-0.0002***	0.0000	0.0002***	0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Horizon 15	-0.0002***	-0.0000	0.0002***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Horizon 16	-0.0004***	-0.0001***	0.0001**	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	4217	4217	4217	4217
F-stat p-value	0.000	0.000	0.000	0.000
R^2	0.522	0.522	0.522	0.522

Panel B: Risk-Adjusted Returns Estimates

	EW		VW	
	(1) Stock	(2) Stock + REITs	(3) Stock	(4) Stock + REITs
PV(GSE Guarantee)	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Value of Guarantees: Pre and Post GFC

Table 4 examines the value-weighted risk-adjusted returns of the GSE mortgage guarantees before and after the GFC using before and after 2010 as a cutoff year. The table presents estimates for both the GPME and Risk-Adjusted Profit methodologies.

	Pre GFC		Post GFC	
GPME				
PV(GSE Guarantee)	-0.009**	(-2.33)	0.012***	(14.78)
Risk-Adjusted Profit				
PV(GSE Guarantee)	-0.009**	(-2.49)	0.020***	(4.57)

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: STACR Deal Characteristics

Table 5 presents the mean characteristics of Freddie MAC STACR tranches. Tranche size is the average size of a given tranche relative to a $1 total face value of the total underlying loan pool. The attachment point is average amount of initial suboridmation a given tranche has before it incurs losses. The detachment point corresponds to the point at which a given tranche incurs its maximum amount of losses. Tranhe Spread is the average interest rate spread paid by a given tranhe. Tranche WAL is the weighted average life in the absence of default assuming a 15% CPR. Tranche market price is the average market price of a given tranche just after issuance. The loss ratio is taken by deducting the PV of the tranche coupon in the absence of default from the market price. Junior corresponds to the most junior sold tranch. Junior-Mezz corresponds to the second most junior sold tranche. Senior corresponds to the most senior sold tranche. Senior-Mezz corresponds to the second most senior sold tranche. Supersenior corresponds to the senior tranche retained by Freddie Mac. All reported values are averages across STACR deals.

	(1) Junior	(2) Junior-Mezz	(3) Senior-Mezz	(4) Senior	(5) Supersenior
Tranche Size	0.0064	0.0091	0.0139	0.0106	0.9575
Tranche Attachment Point	0.0016	0.0080	0.0180	0.0320	0.0425
Tranche Detachment Point	0.0080	0.0171	0.0320	0.0425	1.0000
Tranche Spread	0.0862	0.0429	0.0246	0.0114	.
Tranche WAL	8.9106	6.7602	3.4611	1.1644	.
Tranche Market Price	101.1512	98.7903	99.4067	99.8009	.
Loss Ratio	-68.5793	-27.9278	-8.9128	-1.4840	.
Observations	54	54	54	54	54

Table 6: Market Rate G-Fees from a Structural Credit Estimation

Table 6 estimates the market value of expected losses on GSE mortgages by using the market prices of Freddie Mac STACR reinsurance securitization tranches over 2015-2023. Freddie Mac retains the most senior tranche, so the market price of this tranche must be estimated. Panel A reports estimates when assuming that the most senior tranche is risk-free. Panel B estimates the market value of the most senior tranche and therefore the total market value of expected loan losses using the Nagel and Purnanandam (2020) model to match the prices of the most junior subordinThe model is estimated separately for each STACR deal, and the average estimated model parameters, σ, $A0$, and ρ, are reported.ameters, σ, $A0$, ρ , and λ_1 are reported. Panel C reports estimate using the endogenous prepayment version of the structural model. 'Actual Gfee' is the average Freddie Mac guarantee fee on new acquisitions of single-family mortgages in the year in which a CRT deal is issued. Market Rate Gfee is the annualized market value of expected losses. Gfee subsidy is the difference between the actual g-fee and the market-implied g-fee. All estimates are reported in basis points.

Panel A: Risk-Free Most Senior Tranche

	(1) Actual Gfee	(2) Market Rate Gfee	(3) Gfee Gap
Estimate	56.907***	24.596***	32.567***
	(0.445)	(1.233)	(1.370)
Observations	54	55	54

Panel B: Structural Credit Valuation

	(1) Actual Gfee	(2) Market Rate Gfee	(3) Gfee Gap
Estimate	56.907***	23.860***	33.047***
	(0.445)	(1.244)	(1.420)
Observations	54	54	54
$\widehat{\sigma}$		0.06	0.06
$\widehat{A0}$		1.30	1.30
$\widehat{\rho}$		0.13	0.13

Panel C: Structural Credit Model with Endogenous Prepayment

	(1) Actual Gfee	(2) Market Rate Gfee	(3) Gfee Gap
Estimate	56.907***	26.357***	30.550***
	(0.445)	(1.083)	(1.234)
Observations	54	54	54
$\widehat{\sigma}$		0.05	0.05
$\widehat{A0}$		1.12	1.12
$\widehat{\rho}$		0.29	0.29
$\widehat{\lambda 1}$		19.45	19.45

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Lender Balance Sheet Constraints and GSE Selling Behavior

Table 7 examines the probability that a mortgage lender sells a conforming eligible loan to the GSEs. 'Guarantee Fee Rate' is the average effective guarantee fee on Freddie Mac single-family mortgages in the year that a mortgage is originated. 'Non-Depository Lender' equals one if a lender is a nonbank. 'Tier 1 Capital Ratio' is the lender's BHC tier 1 capital ratio. 'Bank Size' is the log of the BHC's total assets. 'Deposit Funding Ratio' is the ratio of the BHCs demand and savings deposits to total assets. Bank characteristics are measured in 2012, before the guarantee fee hike, and are standardized for ease of interpretation. When indicated, columns include time, state, county, and lender fixed effects. Standard errors are clustered at the lender level. Data are taken from a 10% random sample of the HMDA dataset covering loans originated from 2008 to 2017.

	P(Sold to GSE)			
	(1)	(2)	(3)	(4)
Guarantee Fee Rate × Non-Depository Lender	0.009***	0.009***		
	(6.88)	(6.65)		
Guarantee Fee Rate × Tier 1 Capital Ratio			-0.001***	-0.001***
			(-2.92)	(-3.21)
Guarantee Fee Rate × Bank Size			-0.005***	-0.005***
			(-2.82)	(-2.90)
Guarantee Fee Rate × Deposit Funding Ratio			-0.004*	-0.004**
			(-1.87)	(-2.00)
Log(Income)	-0.003	-0.004	-0.025**	-0.026**
	(-0.83)	(-0.99)	(-2.33)	(-2.45)
Log(Loan Size)	0.026***	0.029***	0.034	0.045
	(2.86)	(3.35)	(1.14)	(1.63)
Observations	10776938	10710119	2562678	2523957
Time FE	Yes	No	Yes	No
Census × Time FE	No	Yes	No	Yes
Lender FE	Yes	Yes	Yes	Yes
R^2	0.500	0.512	0.397	0.441

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Post-GFC Jumbo-Conforming Spread

Table 8 measures the conforming-nonconforming loan spread using data from the updated HMDA data covering mortgages originated over 2018-2019. The conforming-nonconforming spread is estimated using a regression discontinuity design with a $50,000 bandwidth and linear polynomials on each side of the cutoff. When specified, the columns include 'Controls' consisting of loan-to-value, debt-to-income, loan closing costs, as well as the specified fixed effects. Data were taken from HMDA.

	(Interest Rate Spread)		
	(1)	(2)	(3)
Jumbo	-0.293***	-0.215***	-0.099***
	(-69.37)	(-29.17)	(-15.56)
Observations	346388	327054	326872
Controls	No	Yes	Yes
Year FE	No	Yes	Yes
Tract FE	No	Yes	Yes
Lender FE	No	No	Yes

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: Instrumented Jumbo-Conforming Spread

Table 9 measures the conforming-nonconforming loan spread separately for bank and non-bank originators from the updated HMDA data covering mortgages originated over 2018-2019. Panel A estimates the conforming-nonconforming spread using a regression discontinuity design with the loan amount around the conforming loan limit and a $50,000 bandwidth and linear polynomials on each side of the cutoff. Panel B estimates the conforming-nonconforming spread using a regression discontinuity design following Kaufman (2014) using the home appraisal value around the conforming loan limit divided by 0.80. LTV Jumbo IV is the reduced form regression discontinuity estimate using the home appraisal IV around a $50,000 bandwidth and linear polynomials on each side of the cutoff. $\widehat{Jumbo}$ is the instrumented value of jumbo using the LTV Jumbo IV. When indicated, the columns include 'Controls' consisting of loan-to-value, debt-to-income, loan closing costs, as well as the indicated fixed effects. Data were taken from HMDA.

	Banks			Non-Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
Jumbo	-0.279***	-0.178***	-0.113***	-0.117***	-0.104***	-0.102***
	(-63.23)	(-35.88)	(-24.33)	(-15.44)	(-13.36)	(-13.96)
Observations	130302	118638	118493	216086	201139	201092
Controls	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Tract FE	No	Yes	Yes	No	Yes	Yes
Lender FE	No	No	Yes	No	No	Yes

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

	Banks			Non-Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
LTV Jumbo IV	-0.014***			0.014***		
	(-2.92)			(3.24)		
$\widehat{Jumbo}$		-0.111***	-0.104***		0.362***	0.316***
		(-2.93)	(-2.82)		(3.22)	(2.95)
Observations	88846	88846	88690	142930	142930	142879
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	No	No	Yes	No	No	Yes

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Internet Appendix

A Cash Flow Valuation for Fannie Mae Guarantees

Table A1: Cash Flow Summary Statistics

Table A1 reports summary statistics for Fannie Mae loan guarantee cash flows. 'Weighted Average Life' is the length of years of the average outstanding principal balance of the loans that Fannie insures. 'Total Cash Back' is the raw amount of cash flows that Fannie received from insuring loans that were originated in a given quarter. 'Guarantee Fee' is the average guarantee fee on new mortgage originations in a given quarter. 'Risk-Free Dollar PV' is the present value in dollar terms ($ millions) of the GSE guarantees computed using the term structure of risk-free rates. 'Risk-Free PV' is the present value per $1 of mortgage guaranteed.

	Mean	SD	Min	P25	P50	P75	Max	N
Total Loan Principal Guaranteed ($ Billions)	72.25	37.46	25.34	47.37	63.12	92.77	224.39	76
Weighted Average Life	4.20	1.08	2.05	3.42	4.19	5.02	5.96	76
Total Cash Back ($ Billions)	0.73	1.06	-1.67	0.08	0.71	1.39	3.57	76
Guarantee Fee (bps)	35.09	16.58	19.00	21.50	25.70	57.20	62.90	76
Risk-Free PV	0.008	0.01	-0.027	0.002	0.008	0.020	0.034	76
Risk-Free Dollar PV	733	969.83	-1385	85	682	1336	3436	76

Figure A1: Average Fannie Mae Guarantee Net Cash Flow by Horizon

Figure A1 plots the average net cash flow distribution of the GSE guarantees by years since the loan was originated.

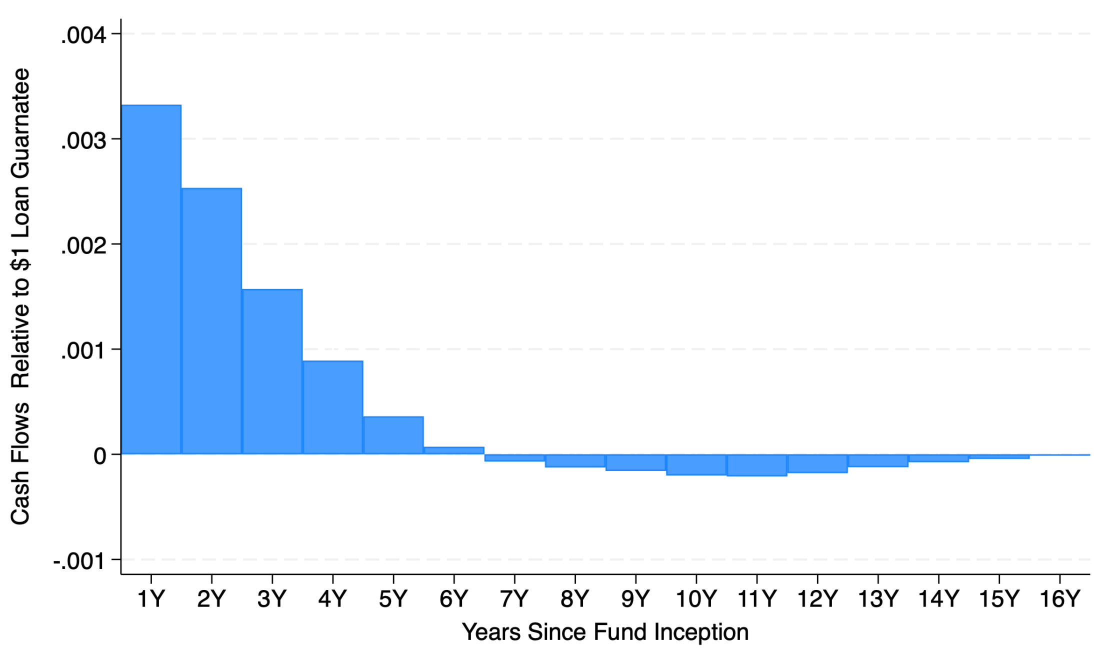


Table A2: Value of Fannie Mae Guarantees: GPME

Table A2 estimates the value of the Fannie Mae guarantee cash flows using GPME. Panel A presents equal weighted results and Panel B presents the value-weighted results using the principal amount of loan guaranteed as a weight. Columns (1)-(3) estimate the specification using different risk factors and column (4) estimate an SDF using all three risk factors. The estimated SDF parameters are presented below the table.

Panel A: EW

	PV			
	(1) Stocks	(2) REITs	(3) MREITs	(4) All
PV(GSE Guarantee)	0.003*	0.004*	0.004*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)

Panel B: VW

	PV			
	(1) Stocks	(2) REITs	(3) MREITs	(4) All
PV(GSE Guarantee)	0.005***	0.007***	0.007***	0.005***
	(0.001)	(0.002)	(0.002)	(0.001)
$b1$	0.04	0.03	0.00	0.04
$b2$	2.89	1.00	1.19	0.21
$b3$				-0.06
$b4$				2.78

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A3: Value of Fannie Mae Guarantees: RAP

Table A3 reports the risk loadings and corresponding Fannie Mae guarantee risk-adjusted valuation from the risk-adjusted profit methodology. Panel A reports the risk loadings for the baseline specification that includes the a_h horizon intercepts for ZCB bonds, Stock (CRSP VW stock returns), MREIT (Nareit MREIT benchmark returns), and REIT (Nareit REIT benchmark returns). Panel B reports both the total risk-adjusted valuation. Columns (1) and (2) are equal-weighted estimates and Columns (3) and (4) are value-weighted estimates. The reported risk loadings coresspond to the point estimates in Columns (2) and (4) that include all the benchmark returns. Columns (1) and (3) only include the Treasury and stock market benchmarks. Standard errors are in parentheses and computed using a non-parametric block bootstrap procedure.

Panel A: Risk-Loadings

	ZCB	Stock	MREIT	REIT
	(1)	(2)	(3)	(4)
Horizon 1	0.0008***	0.0013***	0.0001	-0.0009***
	(0.0000)	(0.0003)	(0.0003)	(0.0003)
Horizon 2	0.0006***	0.0010***	0.0000	-0.0004*
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Horizon 3	0.0002***	0.0012***	0.0002	-0.0003
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Horizon 4	-0.0000	0.0012***	0.0004*	-0.0004
	(0.0001)	(0.0002)	(0.0002)	(0.0003)
Horizon 5	-0.0002*	0.0008***	0.0006**	-0.0004
	(0.0001)	(0.0001)	(0.0003)	(0.0003)
Horizon 6	-0.0002**	0.0006***	0.0006***	-0.0003
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Horizon 7	-0.0002***	0.0004***	0.0004***	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Horizon 8	-0.0002***	0.0002***	0.0003***	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Horizon 9	-0.0001***	0.0002**	0.0002***	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Horizon 10	-0.0001***	0.0001	0.0002***	-0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Horizon 11	-0.0001***	0.0000	0.0002***	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Horizon 12	-0.0001***	0.0000	0.0001***	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Horizon 13	-0.0000***	0.0000	0.0001***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Horizon 14	-0.0000***	0.0000	0.0000**	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Horizon 15	-0.0000**	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Horizon 16	-0.0000***	0.0000***	-0.0000***	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	3589	3589	3589	3589
F-stat p-value	0.000	0.000	0.000	0.038
R^2	0.579	0.579	0.579	0.579

Panel B: Risk-Adjusted Returns Estimates

	EW		VW	
	(1) Stock	(2) Stock + REITs	(3) Stock	(4) Stock + REITs
PV(GSE Guarantee)	0.008***	0.008***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A4: Value of Fannie Mae Guarantees: Pre and Post GFC

Table A4 examines the value-weighted risk-adjusted returns of the GSE mortgage guarantees before and after the GFC using 2010 as a cutoff year. The table presents estimates for both the GPME and Risk-Adjusted Profit methodologies.

	Pre GFC		Post GFC	
GPME				
PV(GSE Guarantee)	-0.001	(-0.67)	0.014***	(15.91)
Risk-Adjusted Profit				
PV(GSE Guarantee)	0.000	(0.07)	0.022***	(5.43)

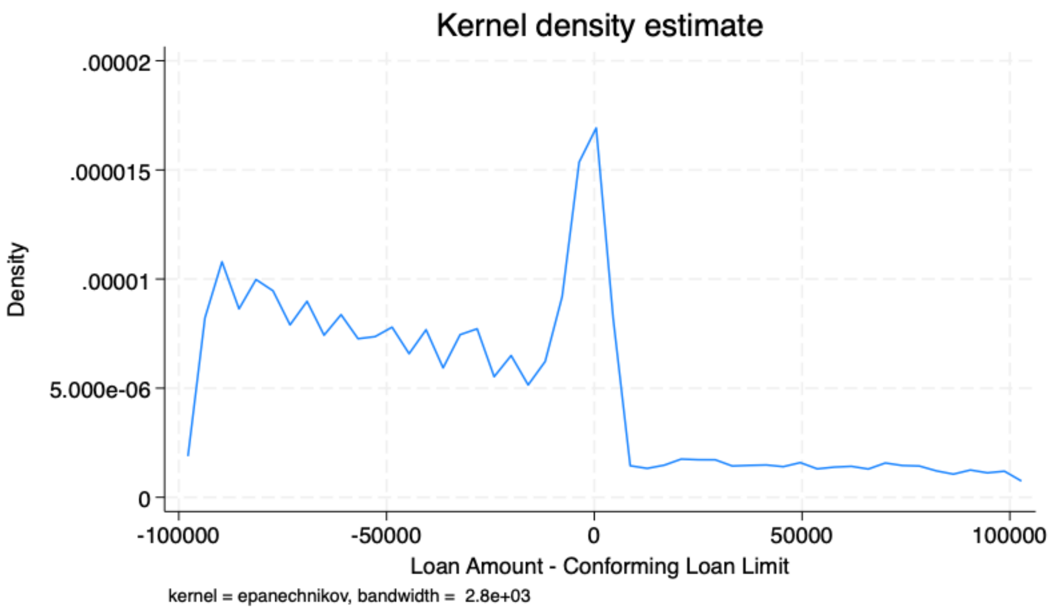
t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

B Additional Jumbo-Conforming Spread Results

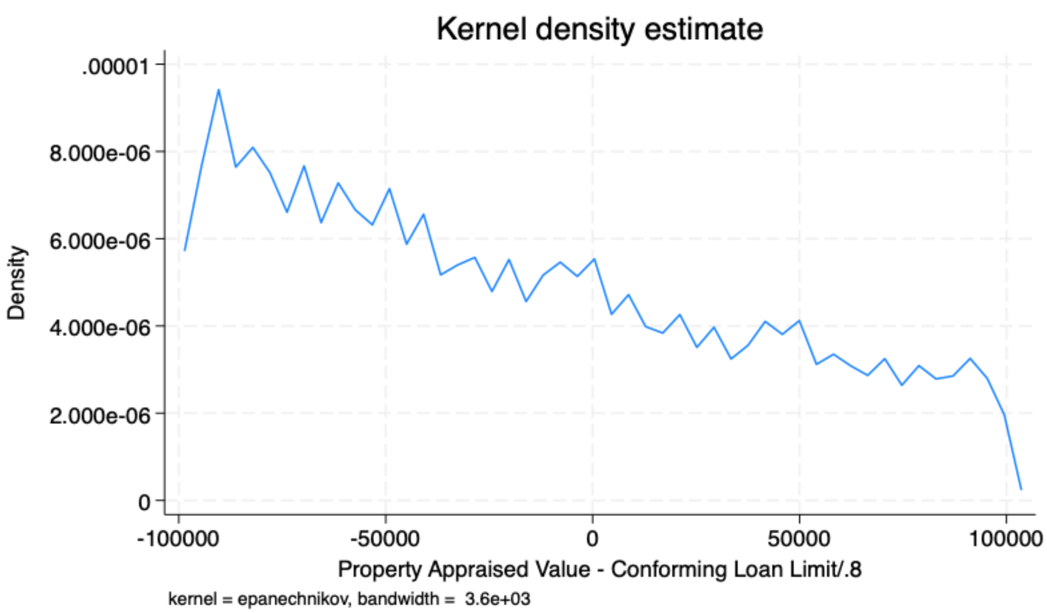
Figure A2: RDD Bandwidth Density Distribution

These figures plot the kernel density of the running variables used to estimate the jumbo-conforming loan spread. Panel (A) plots the distribution of the running variable (Loan Amount - Conforming Loan Limit), and Panel (B) plots the distribution of the instrument running variable (Property Value - Conforming Loan Limit/.8).

(a) Panel A: Loan Amount Running Variable

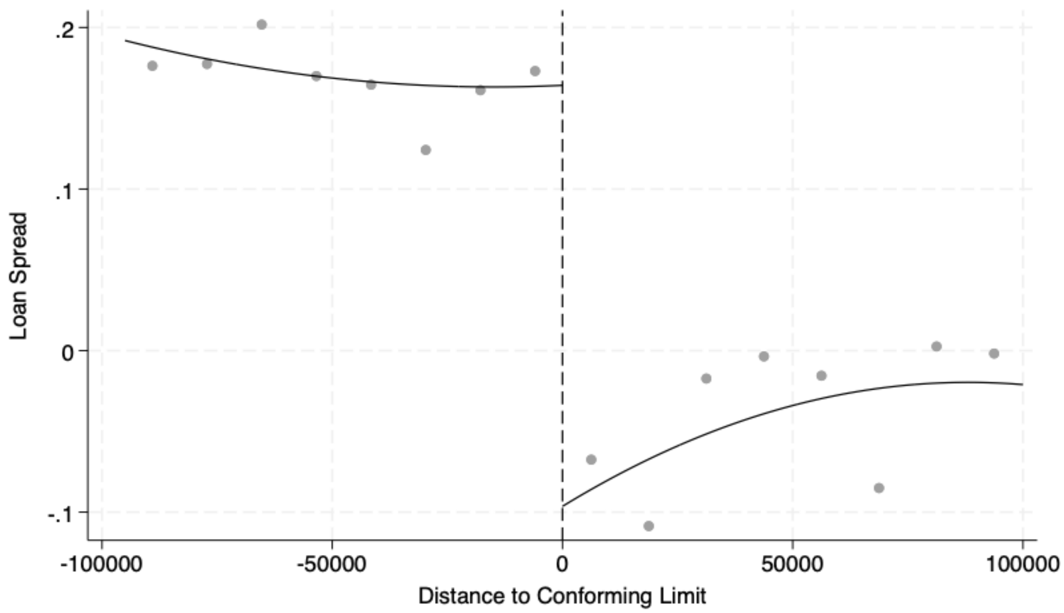


(b) Panel B: Home Appraisal Running Variable



This figure plots the discontinuities in the conforming and nonconforming loans separately for banks and non-banks over the sample period 2018-2022.

(a) Panel A: Banks



(b) Panel B: Non-Banks

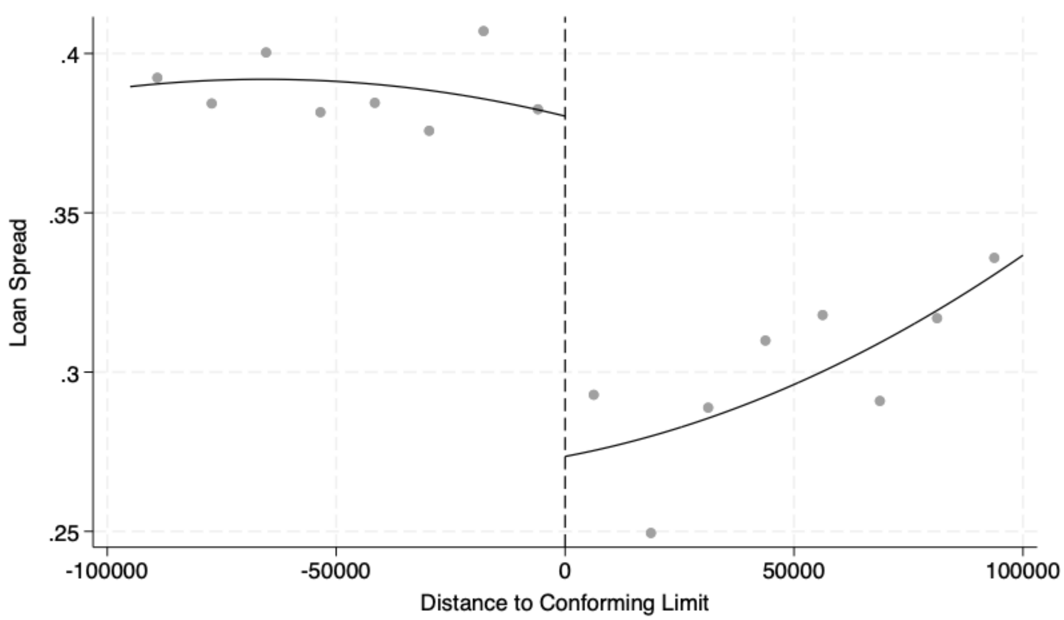


Figure A4: Jumbo-Conforming Spread Over Time

This figure plots the time series of the estimated jumbo-conforming loan spread. The conforming-nonconforming spread is estimated using a $50,000 bandwidth around the conforming loan limit and linear polynomials on each side of the cutoff. I estimate the conforming-nonconforming spread post-2018 using the updated HMDA data, which also allows me to break lender types by bank and non-bank lenders. I estimate the conforming-nonconforming spread pre-2018 using the MIRS dataset.

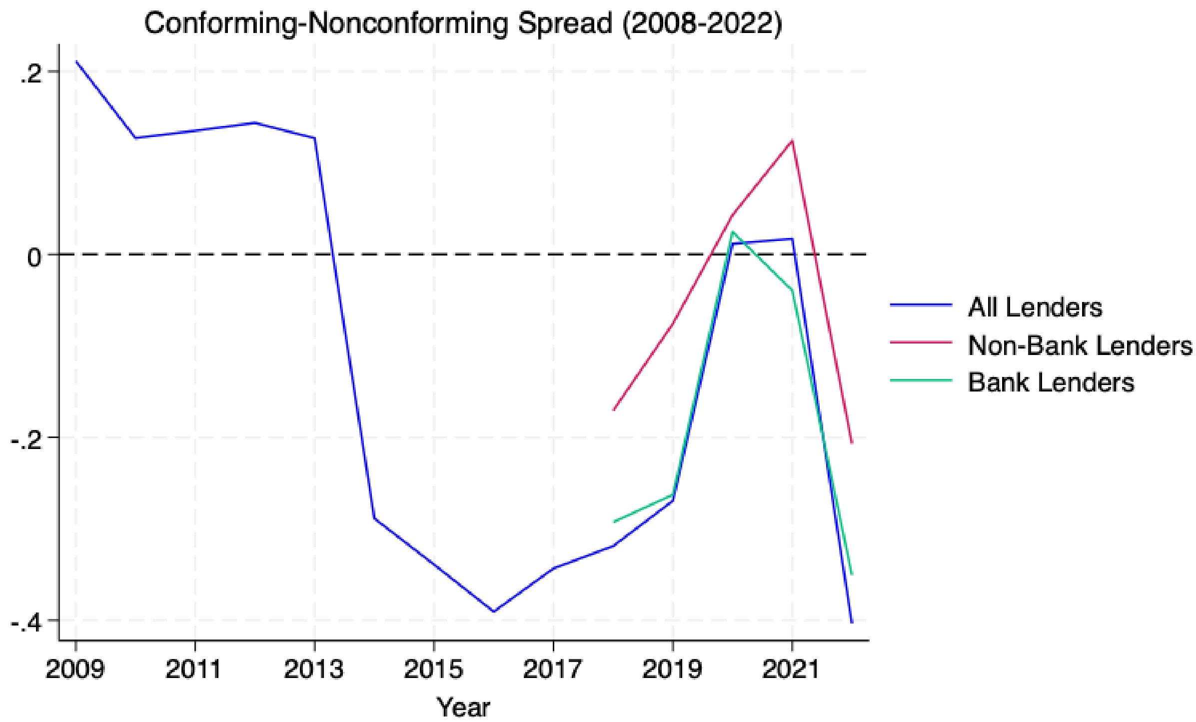


Table A7: Instrumented Jumbo-Conforming Spread: Drop 5 Largest Banks

Table A7 measures the conforming-nonconforming loan spread separately for bank originators after dropping the 5 largest banks in the sample in terms of the number of mortgage originations. The table estimates the conforming-nonconforming spread using a regression discontinuity design following Kaufman (2014) using the home appraisal value around the conforming loan limit divided by 0.80. LTV Jumbo IV is the reduced form regression discontinuity estimate using a \$50,000 bandwidth and linear polynomials on each side of the cutoff. $\widehat{Jumbo}$ is the instrumented value of jumbo using the Appraisal IV. When specified, the columns include 'Controls' consisting of loan-to-value, debt-to-income, loan closing costs, as well as the specified fixed effects. Data were taken from HMDA.

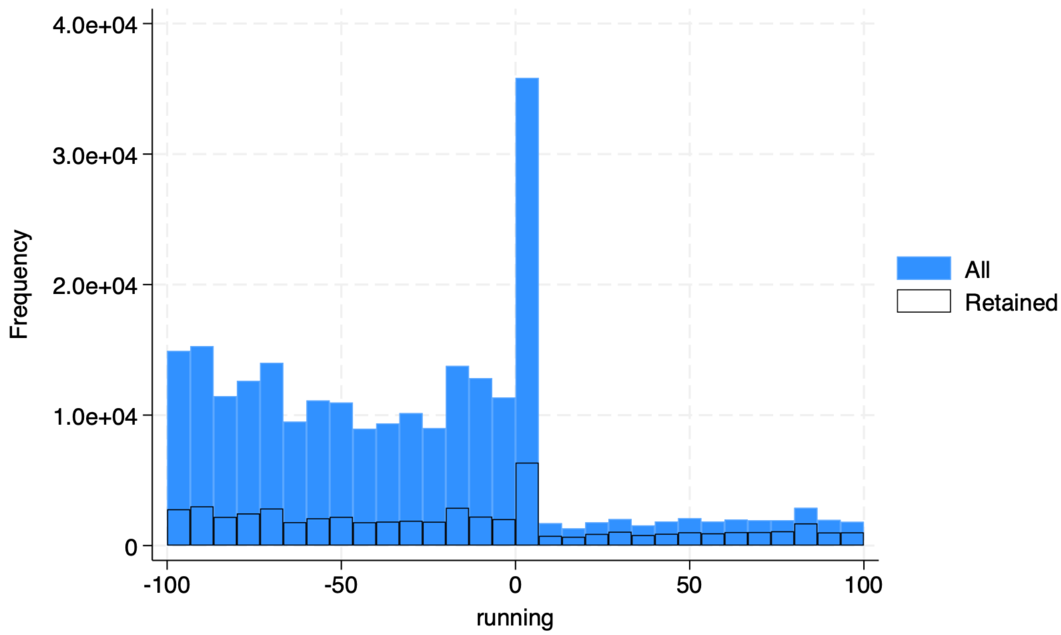
	Banks	
	(1)	(2)
LTV Jumbo IV	-0.011*	
	(-1.78)	
$\widehat{Jumbo}$		-0.129*
		(-1.77)
Observations	50162	50162
Controls	Yes	Yes
Year FE	Yes	Yes
Tract FE	Yes	Yes
Lender FE	Yes	Yes

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

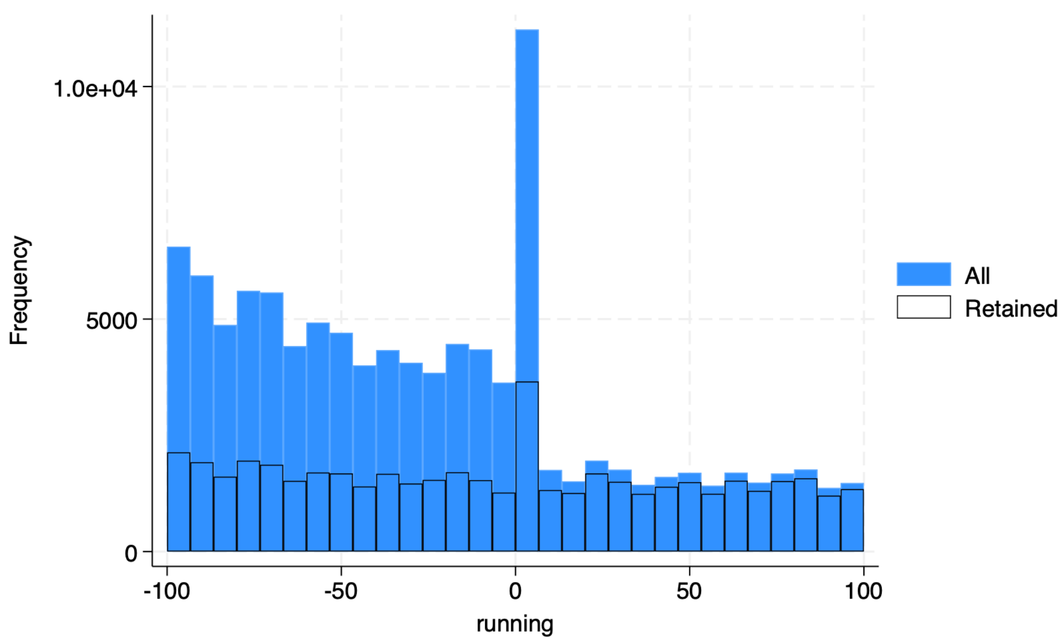
Figure A5: Bunching and Loan Retention

These histograms plot the distribution of loan amounts around the conforming loan limit for all bank loans, as well as the subset distribution of loans that banks retained on the balance sheet.

(a) Panel A: Pre-inversion (2009-2013)



(b) Panel B: Post-inversion (2015-2017)



C Additional Structural Credit Risk Model Results

Table A8: Structural Credit Estimation: Drop Superjunior Subsample

Table A8 reports the previous STACR estimates for the subsample of deals that have no superjunior tranches retained by Freddie Mac. Freddie Mac retains the most senior tranche, so the market price of this tranche must be estimated. Panel A reports estimates when assuming that the most senior tranche is risk-free. Panel B estimates the market value of the most senior tranche and therefore the total market value of expected loan losses using the Nagel and Purnanandam (2020) model to match the prices of the most junior subordinate tranches. The model is estimated separately for each STACR deal, and the average estimated model parameters, σ, $A0$, and ρ, are reported.ameters, σ, $A0$, ρ , and λ_1 are reported. Panel C reports the estimate using the endogenous prepayment version of the structural model. 'Actual Gfee' is the average Freddie Mac guarantee fee on new acquisitions of single-family mortgages in the year in which a CRT deal is issued. Market Rate Gfee is the annualized market value of expected losses. Gfee subsidy is the difference between the actual g-fee and the market-implied g-fee. All estimates are reported in basis points.

Panel A: Risk-Free Most Senior Tranche

	(1) Actual Gfee	(2) Market Rate Gfee	(3) Gfee Gap
Estimate	53.938***	32.951***	20.986***
	(0.382)	(1.821)	(1.585)
Observations	16	16	16

Panel B: Structural Credit Valuation

	(1) Actual Gfee	(2) Market Rate Gfee	(3) Gfee Gap
Estimate	53.938***	33.023***	20.915***
	(0.382)	(1.822)	(1.584)
Observations	16	16	16
$\widehat{\sigma}$		0.05	0.05
$\widehat{A0}$		1.21	1.21
$\widehat{\rho}$		0.08	0.08

Panel C: Endogenous Prepayment

	(1) Actual Gfee	(2) Market Rate Gfee	(3) Gfee Gap
Estimate	53.938***	34.050***	19.887***
	(0.382)	(1.807)	(1.594)
Observations	16	16	16
$\widehat{\sigma}$		0.03	0.03
$\widehat{A0}$		1.05	1.05
$\widehat{\rho}$		0.22	0.22
$\widehat{\lambda 1}$		13.91	13.91

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A9: Structural Credit Estimation: Include CNL Constraint

Table A9 reports the previous STACR endogenous prepayment estimates imposing the cumulative net loss (CNL) constraint in the model. Freddie Mac retains the most senior tranche, so the market price of this tranche must be estimated. The table estimates the market value of the most senior tranche and therefore the total market value of expected loan losses using the Nagel and Purnanandam (2020) model to match the prices of the most junior subordinate tranches. The model is estimated separately for each STACR deal, and the average estimated model parameters, σ, $A0$, and ρ, are reported.ameters, σ, $A0$, ρ , and λ_1 are reported. 'Actual Gfee' is the average Freddie Mac guarantee fee on new acquisitions of single-family mortgages in the year in which a CRT deal is issued. Market Rate Gfee is the annualized market value of expected losses. Gfee subsidy is the difference between the actual g-fee and the market-implied g-fee. All estimates are reported in basis points.

	(1) Actual Gfee	(2) Market Rate Gfee	(3) Gfee Gap
Estimate	56.907***	26.246***	30.661***
	(0.445)	(1.171)	(1.293)
Observations	54	54	54
$\widehat{\sigma}$		0.04	0.04
$\widehat{A0}$		1.11	1.11
$\widehat{\rho}$		0.32	0.32
$\widehat{\lambda 1}$		14.49	14.49

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A10: Structural Credit Estimation: Prepayment Kink

Table A10 reports the previous STACR endogenous prepayment estimates when imposing a 3% prepayment cost in the prepayment intensity function. Freddie Mac retains the most senior tranche, so the market price of this tranche must be estimated. The table estimates the market value of the most senior tranche and therefore the total market value of expected loan losses using the Nagel and Purnanandam (2020) model to match the prices of the most junior subordinate tranches. The model is estimated separately for each STACR deal, and the average estimated model parameters, σ, $A0$, and ρ, are reported.ameters, σ, $A0$, ρ , and λ_1 are reported. 'Actual Gfee' is the average Freddie Mac guarantee fee on new acquisitions of single-family mortgages in the year in which a CRT deal is issued. Market Rate Gfee is the annualized market value of expected losses. Gfee subsidy is the difference between the actual g-fee and the market-implied g-fee. All estimates are reported in basis points.

	(1) Actual Gfee	(2) Market Rate Gfee	(3) Gfee Gap
Estimate	56.907***	26.259***	30.649***
	(0.445)	(1.271)	(1.378)
Observations	54	54	54
$\widehat{\sigma}$		0.03	0.03
$\widehat{A0}$		1.07	1.07
$\widehat{\rho}$		0.33	0.33
$\widehat{\lambda 1}$		10.65	10.65

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A11: AR(1) Calibration for Vasicek Process

Table A11 estimates an AR(1) process using monthly 3 month treasury bond rates to calibrate the Vasicek (1977) rate process. The resulting parameters are $\kappa_r = 0.0932$, $\theta_r = 0.01654$, and $\sigma_r = 0.00723$.

	(1) F.DGS3MO
DGS3MO	0.9923***
	(0.0050)
Constant	0.0128
	(0.0163)
Observations	373
R-squared	0.9908
Root MSE	0.2087

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$