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HOUSING SPECULATION, GSES, AND CREDIT MARKET SPILLOVERS

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ABSTRACT

In 2021, the U.S. Treasury reduced the exposure of government-sponsored enterprises (GSEs) to speculative mortgages. As a result, GSE purchases of these loans fell by about 20 percentage points. The consequent decline in credit to speculators, however, was mitigated both by entry of corporate investors and because banks began holding more of these loans. By increasing bank exposure to local risk, this move reduced banks' willingness to supply both jumbo mortgages and small business loans. Our empirical design fully accounts for risks at the balance sheet level. Banks thus manage credit not only in a macro sense — the focus of most research — but also market by market.

*Corresponding author: natee.amornsiripanitch@phil.frb.org. This Philadelphia Fed working paper represents preliminary research that is being circulated for discussion purposes. The views expressed in this paper are solely those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia, the Federal Reserve Board, or the Federal Reserve System. Any errors or omissions are the responsibility of the author. No statements here should be treated as legal or investment advice.

1. INTRODUCTION

Housing prices rose at the fastest rate ever recorded during the period surrounding the COVID-19 pandemic. This led to a rapid expansion of loans purchased by the government-sponsored enterprises (GSEs). During the early quarters of the pandemic, speculative transactions also rose sharply. Figure 1 reports trends in housing speculation, approximated by the share of non-owner-occupied housing transactions.[1] Although levels never reached the highs seen before the global financial crisis of 2008, which was fueled by a credit boom (Mian and Sufi, 2022), the sharp increase in speculation compounded the rising risk exposure at the GSEs. This paper studies how caps instituted in 2021 on GSE mortgage purchases of loans for housing speculators affected these trends. As Figure 1 shows, the speculative share declined in the middle of 2021, coincident with the policy we study. We show that this decline is due to the policy. Beyond that, we emphasize the policy's spillovers to other parts of the credit markets.

At the end of the Trump administration, the U.S. Treasury — the residual claimant in the GSEs — initiated a policy to strengthen GSE capital ratios and reduce their risk, with the ultimate aim of moving them out of government conservatorship and back into private hands.[2] The policy was implemented by amending the Preferred Stock Purchase Agreement (PSPA), which we describe in detail below. Its core changes imposed caps on the GSEs' ability to invest in both high-risk loans (limiting exposure to low credit score borrowers, high loan-to-value loans, and high debt-to-income borrowers) and loans for housing speculation (defined as loans for either second homes or investment properties). We study the impact of these changes on credit supply, housing

[1] We define speculative transactions in the real estate market as household purchase of non-owner-occupied homes (Defusco, Nathanson, and Zwick, 2022). This method has been widely used in the literature (Gao, Sockin, and Xiong, 2020) and is considered as the real-time proxy for speculative housing investment (Guren, 2022).
[2] Both the Obama and Trump administrations made efforts to reprivatize Fannie Mae and Freddie Mac. As of this writing, the two GSEs remain under government ownership and control.

transactions, and local real outcomes. Our results imply that the GSEs provided subsidies to the speculative segments of the U.S. mortgage market, as we find large adjustments by banks when they exit these segments. We also find important second-order effects, as the changes in GSE policies spill over into unaffected segments of credit markets, including low-risk mortgages, high-risk but non-speculative mortgages, jumbo mortgages, and small business lending.

We first test whether the policy change worked as intended. Lenders reduce their sales to the GSEs of speculative mortgages — defined as second homes or homes bought for investment — during the period of policy implementation, but the policy has little impact on sales of non-speculative mortgages to high-risk borrowers. This non-result squares with existing evidence (which we verify) that the limits on high-risk mortgages under the PSPA were rarely binding before the pandemic (Golding et al., 2021); hence, this part of the policy matters little. There is little evidence of pre-trends, although our ability to fully explore this standard diagnostic is limited because most of the pre-period is dramatically affected by the pandemic. The quantitative effects are very large, with sales of speculative mortgages to the GSEs falling by about 20 percentage points.

Next, we explore how lenders adjust when the GSEs exit the market. We find very large adjustments across multiple margins, which implies an important subsidy has been removed by the policy.

First, credit supply declines in the affected segment. Interest rates increase on speculative mortgages by about 13 basis points. This increase is statistically large but economically modest. Second, consistent with these higher rates representing lower credit supply, the quantity of speculative credit falls, both statistically *and* economically. Census tracts more exposed to the policy — based on pre-period levels of speculative lending — experience relative declines in both mortgage originations and mortgage applications. A one-standard-deviation increase in treatment intensity for a given tract leads to about 18.2 percent fewer speculative mortgage originations during the policy period, relative to the pre-policy period. The decline in originations is similar in magnitude for applications, which suggests that most of the effects on quantity are happening because lenders discourage some borrowers from applying or simply stop serving the market for second homes or investment properties. And, in fact, we find little change in acceptance rates from the policy.

Second, banks adjust to the removal of the GSE subsidy across multiple margins, thus generating important spillovers to other credit markets. We show: (1) lenders expand credit to both low-risk and high-risk but non-speculative mortgage borrowers; and (2) lenders increase their holdings of mortgages in the affected segments. In other words, lenders continue to originate speculative mortgages, albeit at lower levels than before the policy, and as a result must bear more balance-sheet risk (since the policy prevents their sale to the GSEs). As a consequence, we show that lenders reduce exposure to small business loans. This third adjustment suggests that the policy, by leading banks to become more exposed to local mortgage risk, in turn discourages them from exposure to other local risks like small business loans. We don't find declines in other forms of lending, such as jumbo mortgages, consumer lending, or large commercial lending, but the risks from these segments are easier for banks to diversify, easier to hedge, and easier to pass to third parties, compared with small business loans.[3] For example, consumer lending is heavily securitized, and lending to large businesses is often syndicated.

[3] According to CoreLogic, private-label securitization of jumbo mortgages doubled between 2020 and 2021. The 2021 level was the highest since 2008. See www.corelogic.com/intelligence/2021-a-banner-year-for-jumbo-loan-securitization/.

We then focus on local spillovers, exploiting both granular data from the Community Reinvestment Act (CRA) as well as lending in the jumbo mortgage segment. The CRA data allow us to test how credit origination varies within bank-year. We show that banks with greater exposure to purchase caps for speculative (non-jumbo) mortgages in a given local market — one of the key consequences of the policy — reduce lending to small businesses in that same market. Since this analysis absorbs bank-time effects, it pinpoints the impact of *local* concerns. The same bank supplies less small business credit in markets where it holds greater mortgage risk than it does in markets where it holds less mortgage risk. One possible channel is that banks impose local risk-exposure limits, which in turn means that the need to bear more local risk in speculative mortgages (due to the limits on GSE participation) spills over and constrains the bank's willingness to bear local risk from small business credit.

We also run a parallel set of tests for jumbo loans and find even stronger local effects than for CRA loans. In other words, bank origination of jumbo loans declines in local areas where the bank has greater exposure to purchase caps for speculative (non-jumbo) mortgages, relative to areas with less exposure. This effect seems inconsistent with the local risk channel, in part because overall jumbo lending does not respond to the policy and because private-label securitization (PLS) doubled in 2021 from the previous year, which presumably allows banks to limit their risk exposure to jumbo loans (unlike small business loans). But banks may limit their overall business in markets very exposed to the policy if there are important information synergies across different types of loans. That is, if a bank reduces lending in speculative mortgage markets, this may reduce its general understanding of the local area. Hence, a decline in speculative lending may lead banks to lend less locally for loans not directly affected by the policy.

Third, we explore the policy's effects on local housing activity and local real outcomes. We focus on housing transactions rather than price changes because the policy only stays in effect for three quarters, and housing prices change sluggishly. We show that the policy spurs an increasing share of homes purchased by corporate investors, which replace small investors who used capital to buy second homes and required access to mortgage credit. In addition, transactions in the primary (non-speculative) market increase with treatment exposure, consistent with more credit flowing to that segment rather than to the speculative segments. We also test for, but do not find, declines in the construction sector in more affected areas. We think the limited real effects of the policy reflect two factors. First, as noted, the policy was only in effect for less than one full year (although new constraints were added three months later). Second, the adjustments that we observe, particularly banks' willingness to hold more speculative mortgages in response to the policy and the entry of corporate investors, mitigate real effects by limiting the overall reduction in capital supplied to this market.

Our paper contributes to three strands of the literature. First, we contribute to recent studies of the housing boom during the pandemic. Some papers have emphasized the impact of increased demand for residential properties due to the popularity of working at home, which increased sharply in early 2020 and continues to remain elevated relative to pre-pandemic levels. For example, Gupta et al. (2022) find a flatter pricing gradient between inner cities and outlying suburbs. Mondragon and Wieland (2022), using cross-sectional evidence, attribute about half of the pandemic house-price increases to higher demand from agents working at home. Guren (2022) agrees, arguing that the pandemic housing boom, unlike the run-up before the global financial crisis, did not come from unrealistic pricing expectations but from increased demand running into supply constraints. He argues, for example, that housing speculation was much more prevalent during the early 2000s. Our analysis can help explain why, as the sharp rise in housing speculation ended with the implementation of GSE activity limits in this market.

Beyond the direct effect of the pandemic on demand, monetary interventions led to low interest rates in general, and the aggressive quantitative easing starting in March 2020 dramatically increased the demand for agency-backed mortgage-backed securities from the Federal Reserve. Fuster et al. (2021) use this period to illustrate how operational frictions can raise the wedge between funding costs (which the Federal Reserve can influence) and mortgage supply in the primary markets; they show that these frictions helped technology-based lenders gain market share. Our paper, in contrast to most of this literature, focuses on policies that restrained (rather than fueled) some of these forces by limiting GSE participation in speculative segments of the mortgage markets.

Second, we provide further evidence that GSE activities subsidize mortgage credit. Early research showed that the enhanced liquidity provided by GSE securitization raised credit supply (Loutskina and Strahan, 2009; Loutskina, 2011) and so focused on differences between non-jumbo and jumbo segments of the market. Using a similar approach, several papers focused on the spread differential around the jumbo/non-jumbo cutoff, which has exhibited substantial variation over time (McKenzie, 2002 provides an early survey of this literature). Some argued that the GSEs enhanced the supply of credit to subprime and Alt-A mortgage markets during the 2000–2006 boom by buying high-risk mortgages and also purchasing private-label mortgage-backed securities (Wallison and Calomiris, 2009). Sunderam and Scharfstein (2013) show that the level of pass-through of GSE-funded subsidies to the primary mortgage market, however, can be stymied by lender market power, which increased temporarily after the global financial crisis. Our paper provides the most direct evidence that GSE subsidies affect mortgage credit supply and also that banks adjust across other margins to offset the reduced subsidy.

Third, we are the first to explore the impact of a policy directed toward restraining speculation in the U.S. housing market. In our setting, the policy was motivated by concern about GSE risk but, as a consequence, removed an important subsidy to speculators in housing markets. Most existing studies of government policies have focused on markets in Asia, such as Taiwan, Singapore, and Hong Kong (e.g., Fu, Qian, and Yeung, 2016; Agarwal, Badarinza, and Qian, 2018; Deng, Gyourko, and Li, 2019; Chi, LaPoint, and Lin, 2020; Agarwal et al., 2021). A number of papers that study the U.S. housing market have emphasized the important role speculators play in both volume and house-price dynamics (Nathanson and Zwick, 2018; DeFusco, Nathanson, and Zwick, 2022) as well as their role in mispricing (Chinco and Mayer, 2016) and potentially destabilizing housing markets (Gao, Sockin, and Xiong, 2020; García, 2022; Mian and Sufi, 2022).

2. Setting

The Preferred Stock Purchase Agreement (PSPA) was created when Fannie Mae and Freddie Mac were taken into government conservatorship during the 2008 financial crisis. This agreement outlines the government's commitment to and governance of these two GSEs and grants the government controlling ownership (79.9 percent of common equity). The PSPA was amended several times after 2008 to increase the GSEs' capital buffers, which act to protect taxpayers from losses. Initially, these amendments focused on capital buffers by limiting dividend and other distributions to bolster reserves. On January 14, 2021, the U.S. Treasury, together with the Federal Housing Finance Agency (FHFA), announced additional changes to the PSPA to further strengthen GSE capitalization, along with other changes aimed at limiting the GSEs' risk exposure.

We focus on the 2021 amendment because it went further than earlier adjustments by restricting GSE activities in their core business of acquiring mortgages from private lenders. We focus on purchase caps affecting the following: limiting GSE acquisition of single-family mortgage loans with multiple high-risk metrics to 6 percent of home purchase mortgages and 3 percent of refinancing mortgages (or refis), based on a trailing 52-week period. High-risk mortgages are those with two or more of the following: combined loan-to-value (CLTV) greater than 90 percent; debt-to-income (DTI) ratio greater than 45 percent; and credit score less than 680. In addition, the amendment limits the GSEs' acquisition of mortgages secured by second homes or investment properties (which we will refer to as "speculative mortgages") to 7 percent of single-family acquisitions over the preceding 52-week period. The purchase cap policy went into effect on April 1, 2021, but was suspended in September 2021. In January 2022, the FHFA announced that higher commitment fees (for example, roughly tripling fees for second-home mortgages) for speculative mortgages would be used to limit risk rather than impose hard constraints; this change effectively pushed this policy in the same direction as the original one but with somewhat weaker effects.[4]

Given this history, we limit our regression analysis to the five quarters that surround the initial amendment to the PSPA, running from Q3:2020 to Q3:2021. That last two quarters of 2020 represent the pre-policy period, the first quarter of 2021 represents the announcement period, and the second and third quarters of 2021 represent the treatment period. We do not include data before Q3:2020 because we want to avoid contaminating the results with the large effects of the COVID-19 pandemic on both the housing market and the broader economy. We drop the quarters after

[4] See home.treasury.gov/news/press-releases/sm1236.

Q3:2021 because the policy was first suspended and then reintroduced in a weaker form, making it hard to infer the original policy's effects.

Figure 2 reports aggregate time series patterns in mortgage lending around the policy announcement and implementation dates. Panel A reports the share of GSE mortgage purchases in each of the three categories affected by the policy. The share of speculative mortgages exceeded the 7 percent limit during most quarters leading up to the policy. In contrast, during the pre-policy period the share of high-risk mortgages — both for purchase and for refinance — consistently remained well below the limit imposed by the policy (6 percent for purchase mortgages and 3 percent for refis). As we will show, the policy likely had large effects on credit in the speculative market but limited effects for vanilla high-risk mortgages. We thus begin our formal empirical tests comparing the effect of both policies on credit supply. In later tests, when we consider second-order effects, we focus only on the speculative markets.

Figure 2, Panel B reports the fraction of speculative and high-risk loans sold to the GSEs over time. Consistent with Panel A, *only* speculative mortgages decline during the treatment period (and also during the announcement period). For them, we see a very large drop of about 40 percentage points during the policy period. Both series exhibit sharp increases in the pre-policy period, which we attribute to the effects of the pandemic on housing markets generally. Panel C reports the same figures in total dollar terms. Despite the large decline in sales of speculative mortgages to the GSEs, both the fraction and the amount of speculative mortgage debt held by originating banks increases sharply (see Panels D and E). This means that the decline in speculative mortgage originations is substantially *smaller* than the decline in GSE sales of those mortgages. Thus, these mortgages take up more bank balance-sheet capacity after the policy, which otherwise could have been used for other kinds of loans. As we will show, this effect seems to have displaced lending to small businesses and jumbo mortgages.

Our empirical design exploits the time series variation in the GSE purchase caps when it interacts with cross-sectional heterogeneity in exposure to the policy, as different localities have differential demands for speculative and risky credit. For example, areas with high levels of vacation properties are likely to attract speculative capital in the housing markets. Figure 3 reports a heat map of this heterogeneity at the county level as well as at the census-tract level for three U.S. metropolitan areas (Boston, New York, and Chicago). These measures are built from 2020 data, which reflect speculative activity before the policy's announcement.

3. Empirical Methods and Results

We report tests at the loan level, the geographical level (census tract and county), and the lender level. There are four sets of tests. First, using loan-level data, we estimate the effect of the purchase caps on sales to the GSEs, on loan interest rates, and on loan acceptance rates. Second, we aggregate to the tract level and test how the policy affects origination and application volumes. These two tests establish how the policy affects credit supply in the affected markets. Third, we test how the policy affects bank balance sheets and lending, using aggregation to the bank level. Fourth, we consider how the policy's effect on credit supply affects housing markets and local economies, going back to models aggregated to the census tract (or county) level.

Information on mortgages comes from Home Mortgage Disclosure Act (HMDA) data; we have access to the confidential version (CHMDA), which allows us to observe the date of each loan application. We use data from CoreLogic in some of our tract-level tests because these data allow us to capture housing transactions that are not financed with mortgages (and hence do not appear in the HMDA data), such as all-cash deals as well as those made by corporate investors such as private equity firms.[5] We also access Call Report data to link lending patterns to bank-level characteristics. We use the CRA lending data to obtain granular information on small business loans. Finally, for tests on real effects, we use the U.S. Census Bureau Building Permits Survey to obtain county-level construction permits and Quarterly Census of Employment and Wages data from the U.S. Bureau of Labor Statistics (BLS) to obtain county-level employment information for construction workers. Local gross domestic production (GDP) growth data are from the U.S. Bureau of Economic Analysis.

Table 1 reports summary statistics from the CHMDA data for our samples at the different levels of aggregation. Panel A reports loan-level statistics, Panel B reports statistics at the tract-quarter level, and Panel C reports statistics at the lender-quarter level, where we include only lenders that appear in the Call Reports. Table 2 reports data from CoreLogic (Panel A) and from Call Reports (Panel B).

3.1 GSE Purchase Cap Policy and Mortgage Activities

Following several papers in the mortgage lending literature (Bhutta, Fuster, and Hizmo, 2020; Bhutta, Hizmo, and Ringo, 2021; Bartlett et al., 2022; Amornsiripanitch, 2023), we construct our sample from conventional conforming mortgage applications and originations (i.e., first-lien home purchase, single family, 30-year fixed rate).[6] To ensure that we only include conforming mortgages, we follow the GSE selling guide and loan-level price adjustment (LLPA) documents, and we drop mortgage applications in which the main borrower's credit score is lower than 620, the loan amount exceeds the conforming loan limit, and at least one automated underwriting

[5] GSEs require borrowers to be natural persons in their seller guides. Exceptions include: (1) revocable inter-vivos trusts, (2) HomeStyle Renovation mortgages, and (3) land trusts in those states where the beneficiary is an individual. See selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/Subpart-B2-Eligibility/Chapter-B2-2-Borrower-Eligibility/1032991671/B2-2-01-General-Borrower-Eligibility-Requirements-07-28-2015.htm for Fannie Mae's Selling Guide.

[6] We have run our loan-level tests using conforming refinancing mortgages and find similar results. See Tables IA.2, IA.3, and IA.4 in the Internet Appendix.

system (AUS) flagged the mortgage application as being ineligible for GSE purchase.[7] We also exclude government-guaranteed mortgages such as Veterans Affairs (VA), Federal Housing Administration (FHA), and Farmer Mac mortgages. To make the mortgages more comparable across treatment groups, we drop mortgages with balloon payments, interest-only payments, negative amortization or other non-amortizing features, or prepayment penalties. We keep mortgage applications that were originated or denied between Q3:2020 and Q3:2021, inclusive. Finally, we drop mortgage applications associated with manufactured homes. The filters leave us with approximately 3.75 million home purchase mortgage applications.[8]

We divide our sample into three segments. Speculative mortgages are those backed by second homes or investment properties. Risky mortgages are those backed by primary residences (i.e., non-speculative) but that meet at least two of the following "risky" criteria: (1) cumulative LTV ratio above 90%; (2) debt-to-income ratio above 45%; and (3) credit score lower than 680. The rest we refer to as "safe" mortgages.

To examine whether the GSE purchase cap policy affects lenders' mortgage activities, we run the following loan-level regressions:

$$\begin{aligned} y_{i,t} = \alpha + \partial_j + \delta_k + \gamma_t + \beta_1 Treated_i + \beta_2 Announcement_t \qquad \textit{Eq. 1} \\ + \beta_3 Implementation_t + \beta_4 Treated_i \times Announcement_t \\ + \beta_5 Treated_i \times Implementation_t + Control\,Variables + \epsilon_{i,t}, \end{aligned}$$

where *i* refers to loan and *t* refers to quarter.[9] The dependent variable in Equation (1) is an indicator set to one for rejected applications, an indicator for originated mortgages sold to Fannie Mae or

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[7] See selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/ for Fannie Mae's Selling Guide and singlefamily.fanniemae.com/media/9391/display for the LLPA schedule.

[8] In the period of analysis, there were 4.17 million conventional conforming mortgages (i.e., first-lien home purchase, single family, 30-year fixed rate). Therefore, we end up dropping approximately 10 percent of this sample.

[9] Equation (1) looks on its face like a panel regression, but it is not. We are not following the same loan over time as we need to capture trends, which we do with quarterly fixed effects.

Freddie Mac by the end of the reporting calendar year, or the loan interest rate expressed in basis points. ∂_j, δ_k, and γ_t indicate bank, tract, and quarter fixed effects. We estimate using the linear probability model, given the large number of fixed effects. $Treated - Speculative_i$ equals one if mortgage application i is associated with second/investment homes and zero otherwise, following Gao, Sockin, and Xiong (2020). $Treated - Risky_i$ equals one if mortgage application i is backed by a primary residence property but meets two of the risk metrics defined above. In some columns, we also report models with lender-quarter fixed effects. Control or safe mortgage applications are those associated with conforming mortgages that do not qualify as speculative or risky. $Announcement_t$ equals one for Q1:2021 and zero otherwise; $Implementation_t$ equals one for Q2:2021 and Q3:2021 and zero otherwise.

We also include the following loan-level controls: borrower characteristics such as borrower's age (Amornsiripanitch, 2023), gender, race, ethnicity, credit score, income, and DTI; and loan characteristics such as loan amount, CLTV, whether the application was approved by the AUS, and the number of borrowers. The details on the control variables are described in the Internet Appendix. For brevity, we do not report the coefficients on these variables. Tract, year-quarter, and lender-by-year-quarter fixed effects are included in the regressions, as indicated in the tables. Heteroskedasticity-robust standard errors are clustered at either the geographical or lender levels, again as indicated in the tables.

Recall that Figure 2 suggests that the purchase caps bind for speculative mortgages but not risky mortgages. Table 3 supports this claim, after partialing out fixed effects and control variables. Panel A presents the regression results for GSE sale probability, comparing speculative with safe primary mortgages. In all three columns, the coefficient estimates for *Speculative x Announcement* and *Speculative x Implementation* are large, negative, and statistically significant. After the policy was announced, second/investment home mortgages are much less likely to be sold to the GSEs compared to mortgages for primary residences. The negative effect mostly concentrates on the implementation period (i.e., Q2:2021–Q3:2021). Economically, the probability of second/investment home mortgages sold to the GSEs is 22 percentage points lower than the probability of safe primary mortgages sold to the GSEs after the policy took effect. This represents a reduction of 35 percent when compared with the average sales probability of 62 percent.

Panel B of Table 3 presents the regression results for GSE sale probability of risky relative to safe mortgages. Unlike the results reported in Panel A, the coefficient estimates for *Risky x Announcement* and *Risky x Implementation* are insignificant in all three columns. Consistent with the aggregate trends — which show that the fraction of risky purchased loans (and refinance) is below the caps before the policy — the policy does not significantly affect the probability of risky home purchase mortgages being sold to the GSEs.

Tables 4 and 5 present the regression results for the rejection rate and the interest rate on accepted mortgages. We find no effect of the policy on the rejection rate for speculative mortgages, but we do find a significant decline for risky mortgages. For interest rates, we find higher rates for speculative mortgages during the policy period (about 13 basis points higher) but little effect on interest rates for risky mortgages. The 13 basis-point increase is modest, representing a 4.2 percent increase compared with the average interest rate of 307 basis points.

To help establish causality, Figure 4 plots coefficient estimates (β_t) from the following dynamic version of the loan-level regressions above:

$$y_{i,t} = \alpha + \partial_j + \delta_k + \gamma_t + \sum_t \beta_t Quarter_t \times Speculative_i + \beta_6 Speculative_i + Control\ Variables + \epsilon_{i,t}, \qquad \textit{Eq. 2}$$

where $Quarter_t$ equals one for quarter t and zero otherwise (with Q3:2020 left out as the reference group). ∂_j, δ_k, and γ_t indicate bank, tract, and quarter fixed effects. The β_t coefficients are quarter-specific difference-in-differences (DiD) coefficients, using Q3:2020 as the reference period. As in the earlier models, we estimate Equation (2) with just speculative and safe loans. Figure 4a plots coefficient estimates (β_t) for GSE sale probability. It shows that the significant effects only existed after the policy became effective, suggesting our results are likely causal. Figure 4b plots coefficient estimates (β_t) for application rejections. Consistent with the results reported in Table 3, there is no significant effect on application rejections throughout our sample period. Figure 4c plots coefficient estimates (β_t) for interest rates, and again rates rise only after the policy went into effect. For all three outcomes, there is no evidence of pre-announcement period effects.

Tables 4 and 5 provide some evidence that the policy reduces credit supply for speculative mortgages (because of higher interest rates) and, if anything, *increases* supply for non-speculative but risky mortgages (because of lower rejection rates). This makes sense because the policy itself had a very large effect on lender sales of speculative loans to GSEs, but no effect on their sales of risky but non-speculative loans (Table 3). Hence, banks responded by increasing their willingness to originate those risky loans that they could continue to sell during the policy period.[10] These tests are incomplete, however, because they take the flow of applications as given. Next, we relax this assumption and analyze how purchase caps affect tract-level variation in mortgage volumes.

3.2 Purchase Caps and Mortgage Volume

[10] Table IA.2 in the Internet Appendix presents loan-level regression results for refinance mortgages. The results are qualitatively similar.

We construct a tract-quarter panel data set, starting with all conforming conventional home purchase mortgage applications that were accepted or denied between Q3:2020 and Q3:2021. We sum across loan amounts to compute the total quantity of credit for each tract-quarter cell. Loans are assigned to quarters based on the date on which the lending decision was made. It is important to note that the sample of loan applications that was used in the aggregation process includes loans of all maturities and does not exclude loans with uncommon features such as balloon payments, interest-only payments, negative amortization features, other non-amortizing features, and prepayment penalties. The sample still excludes government-guaranteed mortgages. We relax the data filters here because we are interested in studying the total credit supply of conforming home purchase mortgages that were provided in the sample period.

Tract-quarters with no applications are coded as having zero application volume; hence, our analysis of application volumes represents a balanced panel with all tracts in the U.S. during Q3:2020 through Q3:2021. We code tract-quarters without applications, however, as having missing origination volume because there was no application that the lender could have made lending decisions on. Tract-quarters with non-zero application volumes are coded as having zero origination volume if none of the applications were approved. Panel B of Table 1 provides summary statistics on the sample.

We report regressions analogous to Equation (1) above, although now the models are true panels. The dependent variable equals either the log of one plus the total originations or total applications for tract j in quarter t. Each model is reported separately for quantities based on whether a loan (or a loan application) is part of a treated group (speculative mortgages or non-speculative, risky mortgages) or the control group (safe mortgages). In this framework, we build $Treatment\ Intensity_j$, which measures each tract's exposure to the policy based on the percentage of second/investment home mortgages purchased by the GSEs for mortgages originated in tract j in 2020 (i.e., before the policy announcement).[11] We do not construct a treatment intensity metric for risky loans because the loan-level analysis establishes no effect on sales in this segment. As in the loan-level regressions, $Announcement_t$ equals one for Q1:2021 and zero otherwise; $Implementation_t$ equals one for Q2:2021 and Q3:2021 and zero otherwise.

We include the following control variables at the tract-quarter level within the application pool: median LTV, median DTI, median income, median age, Asian share, Black share, Hispanic share, female share, and share of applications with two borrowers. The details on the control variables are described in the Internet Appendix. Tract and year-quarter fixed effects are included in the regressions. Heteroskedasticity-robust standard errors are clustered at the tract level.

Table 6 presents the results. For the tract-level second/investment home purchase mortgages, the coefficient estimate for *Treatment Intensity x Implementation* is negative and statistically significant (columns 1 and 2). Consistent with the loan-level results, which suggest a negative supply effect, speculative mortgage quantity falls more for tracts with higher exposure to the GSE purchase cap policy. Economically, a one-standard-deviation increase in treatment intensity for a given tract leads to an 18.2 percent (=0.16*1.140) drop in the second/investment home purchase mortgage supply over the policy period (Q2:2021–Q3:2021) compared with the pre-policy period (Q3:2020–Q4:2020). We find similar effects during the announcement period.

The results are opposite for both risky and safe primary home purchase mortgages (columns 3 through 6). Here, the policy encourages more lending in the most affected areas. The coefficient estimate for *Treatment Intensity x Implementation* is positive and statistically

[11] One concern with analysis at the tract level is that areas with more speculation may have experienced faster price appreciation during the pre-period. We find, however, a low correlation across markets between these, and adding a measure of market "hotness" to our model, along with its interactions with the policy shocks, has little impact on the results.

significant in all four columns, meaning that both the risky and safe primary home purchase mortgage quantities rise more in tracts with higher exposure to the GSE purchase cap policy. Economically, a one-standard-deviation increase in treatment intensity for a given tract leads to a 6.6 percent (=0.549*0.12) increase in the risky primary home purchase mortgage supply over the policy period and a 6.1 percent (=0.434*0.14) increase in the safe primary home purchase mortgage supply over the policy period. Since these two segments represent more than 80 percent of the total mortgage market, the results suggest an overall increase in credit in the more affected areas.

Considering that the loan-level results do not indicate a higher rejection rate for second/investment home mortgage applications during the policy period, the above tract-level results may seem surprising. Table 7, which focuses on applications rather than originations, reports very similar effects as Table 6, both statistically and economically. Together with Table 4, these results indicate that most of the reduction in speculative credit supply from the GSE purchase caps occurs from lower application volumes and higher interest rates (see Table 3), rather than because rejection rates increase. This can reflect banks that are discouraging applicants from applying or even banks that are exiting markets with high levels of speculative transactions.

Figure 5 plots coefficients in a dynamic DiD framework similar to Equation (2). Figure 5a plots the coefficient estimates for the tract-level second/investment home purchase mortgage application volume. While the coefficient estimates are statistically significant one quarter before the announcement, the magnitude is small. In contrast, the magnitude of the coefficient estimates increased significantly after the policy was announced. Figure 5b plots coefficient estimates for the tract-level second/investment home purchase mortgage origination. These show that the significant effects only existed after the policy became effective.

To summarize: Purchase caps bind strongly on speculative mortgage activity by the GSEs leading to credit contraction in that segment, as evidenced by higher interest rates and lower application and origination volumes for affected loans and for areas with high levels of pre-policy speculation. In contrast, although the purchase caps policy nominally limits other classes of risky loans, these caps do not bind. As a result, we see no change in GSE sales of risky loans and see *increases* in credit supplied to risky borrowers where the speculative caps are most binding. Similarly, credit supplied to the safe mortgage segment also increases with these caps.

3.3 Spillovers: Bank Risk and Other Lending

In our third set of tests, we analyze potential spillovers from the policy caps, both to banks and to other credit markets. Banks originate fewer speculative mortgages, we have shown, but the very large decline in sales of these mortgages to the GSEs means that their balance-sheet exposure to these mortgages may have increased and, thus, their risk exposure increased. Changes in bank risk exposure, in turn, can affect credit supplied to other lending segments. We thus test how bank balance sheets are affected by the purchase caps. We use the same criteria as the previous section to create the sample of loans from CHMDA and aggregate originations to the lender-quarter level. Lenders that appear in both CHMDA and the Call Reports are included in the regressions (mainly banks).

We focus on the total amount of loans originated by banks but *not* sold. As in our tests for tract-level loan volume, we divide these into the two treated groups (speculative and non-speculative, risky mortgages) and the control group (safe mortgages). In addition, we consider whether jumbo mortgage origination and sale activities responded to the treatment. We then report bank-level panel regressions, where the dependent variable equals the log of one plus the amount of loans originated and held by bank l in quarter t in each of the three categories. We define

$Treatment\ Intensity_l$ similarly to the tract-level tests but do so at the lender level rather than the tract level, defined as the percentage of second/investment home mortgages purchased from lender l by one of the GSEs in 2020 (pre-policy).

Table 8 presents the regression results. The coefficient estimate for *Treatment Intensity x Implementation* is positive and statistically significant, suggesting lenders that have higher exposure to the GSE purchase cap policy keep more second/investment home purchase mortgages on their balance sheet. Economically, a one-standard-deviation increase in treatment intensity for a given lender leads to about a 50 percent (=8.491*0.06) increase in keeping the second/investment home purchase mortgage on its balance sheet over the policy period (Q2:2021–Q3:2021) compared with the pre-policy period (Q3:2020–Q4:2020). This represents the increase in the quarterly flow of loans held, which translates into about 0.44 percent of capital for the average bank in our sample. Since the typical mortgage remains on a balance sheet for roughly seven years, the increase would eventually equal about 10 percent of the average bank's capital.[12] For risky and safe primary home purchase mortgages, as well as jumbo mortgages, however, we find no change in balance-sheet exposure. Figure 6 plots the dynamic DiD coefficient, as in the earlier tests. The significant effect is only evident after the policy became effective, consistent with a causal interpretation.[13]

[12] The regression coefficient (8.5) is multiplied by the one-standard-deviation value of the treatment intensity variable (0.06). Call this value the one-standard-deviation effect. Each bank's amount of speculative conforming home purchase mortgages that were originated but unsold during Q3:2020 and Q4:2020, the pre-policy period, is scaled by the bank's 2020 capital, collected from the Call Report (RCON 3210). The scaled value is averaged across all banks, which is 1.74 percent, and multiplied by the one-standard-deviation effect. The result is the 0.88 percent value, which is the policy's one-standard-deviation marginal effect on the average bank's excess holdings of speculative conforming home purchase mortgages, scaled by its 2020 capital. Since the 0.88 percent value is a two-quarter (Q2:2021 and Q3:2021) effect, as set up by the regression, and the average mortgage life is seven years (see callhallfirst.com/learn/mortgage-and-financial-basics/average-mortgage-length/), 0.88 percent is multiplied by 14 to account for the excess holding's long-run effect on the bank's capital, which is 12.32 percent.

[13] The analogous lender-quarter origination volume regression results are presented in Table IA.5 in the Internet Appendix. Consistent with the tract-quarter results, we find that more exposed lenders originated fewer speculative conforming home purchase mortgages in the post-policy period.

The increase in risk exposure for banks suggests that the GSE purchase cap policy could limit other kinds of credit supplied. To test this idea, we use Call Reports data to build loan-growth measures. We focus on both $Mortgage\ Loan\ Growth_{l,t}$ and $Small\ C\&I\ Loan\ Growth_{l,t}$. $Mortgage\ Loan\ Growth_{l,t}$ equals the growth rate of mortgage loans on the balance sheet of lender l in quarter t; this measure includes all mortgages, as the Call Report does not allow us to separate the data by mortgage product type. $Small\ C\&I\ Loan\ Growth_{l,t}$ is the growth rate of small-size commercial and industrial loans ($1 million or lower) on the balance sheet of lender l in quarter t. We also use the CHMDA data to build the growth in jumbo-loan originations. The explanatory variables of interest are the same as in the earlier models.[14]

Figure IA.1 plots the size distribution of the lenders in our sample and shows that more than half of the lenders have total assets below $1 billion (with median total assets of $0.81 billion). While it is not clear how exactly Fannie Mae and Freddie Mac impose the 7 percent GSE purchase limit on each lender, Freddie Mac mentioned that it only applies this limit on lenders that sold more than five loans secured by second/investment homes in a given month.[15] To account for this additional criterion, we include only lenders above the median size in our regression analyses.

Table 9 presents the regression results for the growth rate of mortgage loans held on the balance sheet (columns 1 and 2) along with small business lending growth (columns 3 and 4) and jumbo (columns 5 and 6). Consistent with Table 8, the coefficient estimate for *Treatment Intensity x Implementation* is positive and statistically significant for mortgages and small loans. That is, mortgage loans on the balance sheet grew more for lenders with higher exposure to the GSE purchase cap policy. This is consistent with what we find using the CHMDA data. Economically,

[14] We have also explored other loan segments, such as consumer lending and overall C&I lending. These growth rates are not affected by the policy, so we do not report these in the tables.
[15] See guide.freddiemac.com/app/guide/bulletin/2021-21 for Freddie Mac implementation of the policy.

a one-standard-deviation increase in treatment intensity for a given lender increases the growth rate of mortgage loans held on the balance sheet by 0.9 percentage point over the policy period (Q2:2021–Q32021) compared with the pre-policy period (Q3:2020–Q4:2020). Jumbo originations do not respond to the policy, however, perhaps because banks use private securitization to insulate these from their higher risk exposure in speculative lending. Figure 7 plots the dynamic DiD coefficients and suggests no evidence that treatment exposure matters before the policy.

The results are the opposite for small business lending, whose growth rate *falls* with policy implementation (columns 3 and 4). A one-standard-deviation increase in treatment intensity for a given lender reduces the growth rate of small commercial and industrial (C&I) loans held on the balance sheet by 2.8 percentage points over the policy period (= -0.36*0.078), compared with an average growth rate of -8.8 percent.

Table 10 presents the regression results for the growth rate of small C&I loans on the balance sheet with different sizes (i.e., \$0–\$100,000, \$100,000–\$250,000, and \$250,000–\$1,000,000). The coefficient estimate for *Treatment Intensity x Implementation* is negative and statistically significant in all six columns, suggesting the effects of the GSE purchase cap policy on small C&I loans exist in every size bracket, although the effects are largest for small C&I loans with sizes ranging from \$250,000 to \$1 million. Figure IA.2 plots the dynamic DiD coefficients and again suggests no evidence that treatment exposure matters before the policy.

3.4 Local Effects

The policy shock presents the opportunity to study whether local shocks specific to one loan type affect credit in other segments. As we have shown, banks restrict credit in the speculative lending market. For small business loans, this leads to a bank-level decline in CRA lending but no change in jumbo loans (recall Table 9). In this section, we strip out any effect on credit at the bank level and test whether any local spillovers remain. A risk channel could generate a spillover to small business lending locally, if banks manage risk at this level. That is, a bank may care not only about its total balance-sheet exposure to a risk class but also about its distribution across markets. In addition, information synergies could motivate banks to cut back across multiple kinds of local loans, even absent a risk channel. Hence, we test for local effects in both small business loans and jumbo mortgages.

To isolate the local channel, rather than estimate the overall effects at the bank-time level, we now test for effects *within* a given bank during a given period and then compare how variation in exposure to speculative mortgages across individual markets affects lending to small business. This approach allows us to capture more potentially confounding effects at both the market level and the bank level (since we can construct a three-dimensional panel). To do so, we exploit data on small business loan and jumbo mortgage originations at the bank-county-year level. With these data, we estimate panel models, as follows:

$$Ln(1+L)_{j,c,t} = \alpha + \partial_{j,t} + \gamma_{c,t} + \beta_1\, Ln(1+Spec.Sold\ to\ GSEs)_{j,2020} \qquad Eq.\ 3$$
$$+\beta_2\big(I_{2021} \times\ Ln(1+Spec.Sold\ to\ GSEs)_{j,2020}\big)$$
$$+\ Control\ Variables + \epsilon_{j,c,t}.$$

The panel varies across banks (*j*), counties (*c*), and years (*t*). Ln(1 + L) is either the log of one plus the origination amount of small business loans or jumbo mortgages. Since these models are estimated with bank-year fixed effects (because of the inclusion of $\partial_{j,t}$), we are comparing how varying exposure to speculative mortgage risk in different markets correlates with a bank's small business loans and jumbo mortgage originations. Hence, we do not need to worry about heterogeneity at the bank level. Moreover, we remove variation in local credit demand by absorbing county-time effects ($\gamma_{c,t}$). As with the earlier measures of treatment exposure, we build each bank's market-by-market exposure to speculative mortgages as of 2020 (*Ln(1 + Spec. Sold to GSEs)*). The direct effect of this variable captures variation in each bank's focus on a given county (therefore, we expect a strong positive correlation), but we also report models with bank-county fixed effects, which absorb this variable. Since we include both bank-time fixed effects and bank-geography fixed effects, reasonable control variables that we could potentially add to the regression are absorbed by these fixed effects. Our coefficient of interest is β_2, which captures the effect of the policy. Since the policy leads banks to hold more speculative mortgages, rather than pass the risk to one of the GSEs, we expect greater exposure during 2020 to lead to reductions in small business lending when the policy comes into effect in 2021.

We obtain small business loan data from the CRA database. This information details small business lending (original amounts up to $1 million) and is broken down at the lender-county-year level. These data are available for banks with total assets greater than $1 billion. Additionally, we use the HMDA data set to calculate the lenders' county-level origination of jumbo loans at the lender-county-year level. We also use the HMDA data to identify the lenders' county-level exposure to the policy. This is based on speculative loans they sold to the GSEs in 2020 at the lender-county level (a time-invariant variable) the year before the policy implementation.

Both the CRA and the jumbo samples are constructed similarly. Using the CRA sample for illustration, we first keep lender-county pairs if there is non-zero CRA lending for them from 2019 to 2021. Next, we expand these pairs into a balanced panel, replacing missing CRA lending data with zeroes. This balanced CRA data set is then combined with the data for 2020 speculative loans sold to the GSEs specific to the lender-county pairs, keeping only those with non-zero values for

2020 speculative loans sold to the GSEs, since these observations do not contribute to the identification of β_2 in Equation 3.[16]

The results in Table 11 and 12 provide strong evidence that banks reduce their exposure to business lending in markets where they have high exposure to speculative mortgages. The fixed effects rule out explanations related to the lender's overall risk exposure or its focus on any given market. As such, these results suggest that banks manage credit at the level of the market as well as at the level of their whole portfolio. The coefficients suggest that a 10 percent increase in exposure to these speculative loans leads to a decline in small business originations of approximately 0.8 percent and in jumbo mortgage originations of approximately 5.5 percent.[17]

3.5 GSE Purchase Cap Policy, Housing Transactions, and Real Effects

In this section we consider the broader potential effects of the purchase caps. First, we model the importance of other investors, namely corporate investors, in the housing market that may be able to substitute for the reduction of investors who rely on bank credit. Second, we test whether the policy has real effects, focusing on employment in the construction sector and construction activity.

We estimate the average quarterly effect of the GSE purchase cap policy on housing investments by using the shares and the total dollar value of housing transactions subdivided into speculative transactions, corporate transactions, and primary transactions, as the outcome variables. Speculative transactions are defined as household purchases of non-owner-occupied

[16] The results are qualitatively similar when we expand the sample to include (1) lender-county pairs that never made any CRA or jumbo mortgage loans between 2019 and 2021 and have non-zero speculative loans to the GSEs in 2020, the treatment exposure, and (2) lender-county pairs that made some CRA or jumbo mortgage loans between 2019 and 2021 but have no treatment exposure. See Tables IA.6 and IA.7 in the Internet Appendix for the results.

[17] Jumbo mortgage lending data are available quarterly in CHMDA, and so we also report these results in the Internet Appendix. See Tables IA.8 and IA.9. The results are quantitatively weaker but qualitatively similar to the lender-county-year results. The weakness may stem from the fact that zooming into the lender-county-quarter level adds more cells that contain zero values, which mechanically reduces the associated variation between the outcome variable and the treatment intensity variable.

homes. We identify household purchases of non-owner-occupied homes based on the buyers' mailing addresses on the deed and the physical addresses of the properties, following Defusco, Nathanson, and Zwick (2022).[18] Corporate transactions are defined based on whether houses are purchased by corporate buyers. We identify corporate buyers based on the corporate buyer indicator provided by CoreLogic. Primary residence transactions are household purchases of owner-occupied properties, again, identified based on comparing the buyers' mailing addresses on the purchase deeds with the physical addresses of the properties. These data represent the entire housing market, including cash-financed deals, as captured by CoreLogic.

In Panel A of Table 13, columns (1) and (2) present the regression results for the tract-level percentage of second/investment home transactions. The coefficient estimate for *Treatment Intensity x Implementation* is negative and statistically significant in both columns, suggesting the percentage of second/investment home transactions drops more for tracts with higher exposure to the GSE purchase cap policy. Economically, a one-standard-deviation increase in treatment intensity for a given tract reduces the percentage of second/investment home transactions by 50 basis points (bps) (= 0.15*0.033), a 2.2 percent drop compared with the sample average percentage of second/investment home transactions (24 percent). As expected, when the outcome variable switches to the tract-level percentage of primary home transactions and corporate transactions, the coefficient estimate for *Treatment Intensity x Implementation* becomes positive and statistically significant, as shown in columns (3)–(6). Interestingly, the magnitude of the coefficient estimate is larger for the percentage of corporate transactions than for the percentage of primary transactions, indicating that corporate buyers are also taking advantage of the policy constraint imposed on second/investment individual homebuyers.

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[18] We cannot apply the other approach (buy and sell within three years) used by Defusco, Nathanson, and Zwick (2022) because of the limitation of our sample period.

Panels B and C report transactions volumes, rather than percentages, in both levels and log levels. Transactions volumes have a strong seasonal component that varies across markets, so we remove this variation, following the procedure outlined in Berger, Turner, and Zwick (2020).[19] These results establish actual substitution away from speculative transactions and toward primary residence transactions (columns 1 through 4), rather than just a decline in speculative activity. The magnitude of the increase in primary residence transactions more than offsets the decline in speculative transactions, which may reflect credit becoming more available for non-speculative mortgages as lenders reallocate capital toward these borrowers (recall Tables 6 and 7). In addition, the increase in transaction activity by corporate investors (columns 5 and 6), who do not rely on the GSEs for capital, may represent similar kinds of investments that had been financed by individuals before the exit of the GSEs.[20] As in the earlier analysis, with one exception, Figure 8 suggests little evidence of any pre-trends. The exception is in the level of speculative transactions, but we do not see this pattern in the share of these transactions.

Table 14 tests for real effects. In particular, we test whether activity in the home building industry is affected by the policy caps. We explore three outcomes: wage and employment in the construction industry and applications for building permits, all of which are available only at the county-quarter level. We keep the same five quarters as our baseline regression, Q3:2020 to Q3:2021. The policy effective period is a dummy variable set to one for Q2:2021 to Q3:2021. The treatment intensity variable is computed using the same method as our treatment intensity

[19] For each county, we first count the number of single-family-house transactions in each quarter of 2019 and compute the mean of those quarterly numbers. We then use the ratio of these individual quarterly numbers of single-family-house transactions over the average quarterly number of transactions as a seasonality-adjusting parameter at the county-quarter level. We divide the actual number of housing transactions in each tract and quarter from Q3:2020 to Q3:2021 by the county-quarter-level seasonality-adjustment parameters to get the seasonally adjusted number of housing transactions in each tract and quarter.

[20] We explore and do not find consistent house price effects, which may stem from the fact that house prices are slow to adjust and that the policy was only in effect for three quarters. Therefore, we only focused on transaction volume, which moves much quicker than prices (Case and Shiller, 1994).

calculation at the tract level but applied at the county level instead. We find no evidence that real economic activity declined because of the policy, although these tests are likely underpowered because we can only measure outcomes by county, which washes out a substantial portion of the variation in treatment exposure.

4. Conclusion

This paper shows that when the GSEs reduced their willingness to buy speculative mortgages in the wake of the 2020 pandemic, credit supply declined in the affected markets, as expected. That said, adjustments to the policy both limited its impact on the affected credit market and led to spillovers to other credit markets. Banks began holding more speculative mortgages than before the policy, reducing the policy's direct negative effect on originations of speculative mortgages, and corporate investors increased their investments in speculative parts of the housing market. Banks' moves to mitigate the loss of business in mortgage speculation, however, increased risk that had formerly been passed to the GSEs. Banks also reduced lending to small businesses and to jumbo mortgage borrowers in local markets where banks were most exposed to speculative loans before the policy went into effect. The empirical design sweeps out risks at the balance-sheet level with granular bank-time fixed effects. As such, the evidence suggests that banks manage credit not only in a macro sense, which has been the main focus of the literature, but also market by market.

REFERENCE

Agarwal, S., Badarinza, C., and Qian, W. (2018). "The effectiveness of housing collateral tightening policy." Working paper. Available at SSRN 2917308.

Agarwal, S., Chau, K. W., Hu, M., and Wan, W. X. (2021). "Tobin tax policy, housing speculation, and property market dynamics." Working paper. Available at SSRN 3641624.

Amornsiripanitch, N. (2023). "The age gap in mortgage access." Federal Reserve Bank of Philadelphia Working Paper 23-03.

Bartlett, R., Morse, A., Stanton, R., and Wallace, N. (2022). "Consumer-lending discrimination in the fintech era." *Journal of Financial Economics* 143(1), 30–56.

Berger, D., Turner, N., and Zwick, E. (2020). "Stimulating housing markets." *Journal of Finance* 75(1), 277–321.

Bhutta, N., Fuster, A., and Hizmo, A. (2020). "Paying too much? Price dispersion in the US mortgage market." FEDS Working Paper No. 2020-62.

Bhutta, N., Hizmo, A., and Ringo, D. (2021). "How much does racial bias affect mortgage lending? Evidence from human and algorithmic credit decisions." *Finance and Economics Discussion Series 2022-067.* Washington: Board of Governors of the Federal Reserve System, doi.org/10.17016/FEDS.2022.067.

Case, K. E., and Shiller, R. J. (March 1994). "A decade of boom and bust in the prices of single-family homes: Boston and Los Angeles, 1983 to 1993." *New England Economic Review*, 40–51.

Chi, C. C., LaPoint, C., and Lin, M. J. (2020). "Flip or flop? Tobin taxes in the real estate market." Working paper. Available at SSRN 3761226.

Chinco, A. and Mayer, C. (2016). "Misinformed speculators and mispricing in the housing market." *Review of Financial Studies 29*(2), 486–522.

DeFusco, A.A., Nathanson, C.G., and Zwick, E. (2022). "Speculative dynamics of prices and volume." *Journal of Financial Economics 146*(1), 205–29.

Deng, Y., Gyourko, J., and Li, T. (2019). "Singapore's cooling measures and its housing market." *Journal of Housing Economics* 45, 101573.

Fu, Y., Qian, W., and Yeung, B. (2016). "Speculative investors and transactions tax: Evidence from the housing market." *Management Science* 62(11), 3254–70.

Fuster, A., Hizmo, A., Lambie-Hanson, L., Vickery, J., and Willen, P. S. (2021). "How resilient is mortgage credit supply? Evidence from the COVID-19 pandemic." National Bureau of Economic Research Working Paper No. 28843.

Gao, Z., Sockin, M., and Xiong, W. (2020). "Economic consequences of housing speculation." *Review of Financial Studies* 33(11), 5248–87.

García, D. I. (2022). "Second-home buying and the housing boom and bust." *Real Estate Economics* 50(1), 33–58.

Golding, E., Goodman, L., Walsh, J., and Choi, J. H. (2021). *The preferred stock purchase agreements will hamper access to credit: A further modification is in order*. Washington, D.C.: Urban Institute.

Gupta, A., Mittal, V., Peeters, J., and Van Nieuwerburgh, S. (2022). "Flattening the curve: Pandemic-induced revaluation of urban real estate." *Journal of Financial Economics* 146(2), 594–636.

Guren, A. M. (2022). “Discussion of ‘What have they been thinking? Homebuyer behavior in hot and cold markets: A ten-year retrospect’ by Robert J. Shiller and Anne K. Thompson.” *Brookings Papers on Economic Activity*.

Loutskina, E. (2011). “The role of securitization in bank liquidity and funding management.” *Journal of Financial Economics* 100(3), 663–84.

Loutskina, E., and Strahan, P. E. (2009). “Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations.” *Journal of Finance* 64(2), 861–89.

McKenzie, J. A. (2002). “A reconsideration of the jumbo/non-jumbo mortgage rate differential.” *Journal of Real Estate Finance and Economics* 25(2-3), 197–213.

Mian, A., and Sufi, A. (2022). “Credit supply and housing speculation.” *Review of Financial Studies* 35(2), 680–719.

Mondragon, J. A., and Wieland, J. (2022). “Housing demand and remote work.” National Bureau of Economic Research Working Paper No. 30041.

Nathanson, C. G., and Zwick, E. (2018). “Arrested development: Theory and evidence of supply-side speculation in the housing market.” *Journal of Finance* 73(6), 2587–633.

Sunderam, A., and D. Scharfstein. (2013). “Concentration in mortgage lending, refinancing activity and mortgage rates.” National Bureau of Economic Research Working Paper No. 19156.

Wallison, P. J., and Calomiris, C. W. (2009). “The last trillion-dollar commitment: The destruction of Fannie Mae and Freddie Mac.” *Journal of Structured Finance*, 15(1), 71–80.

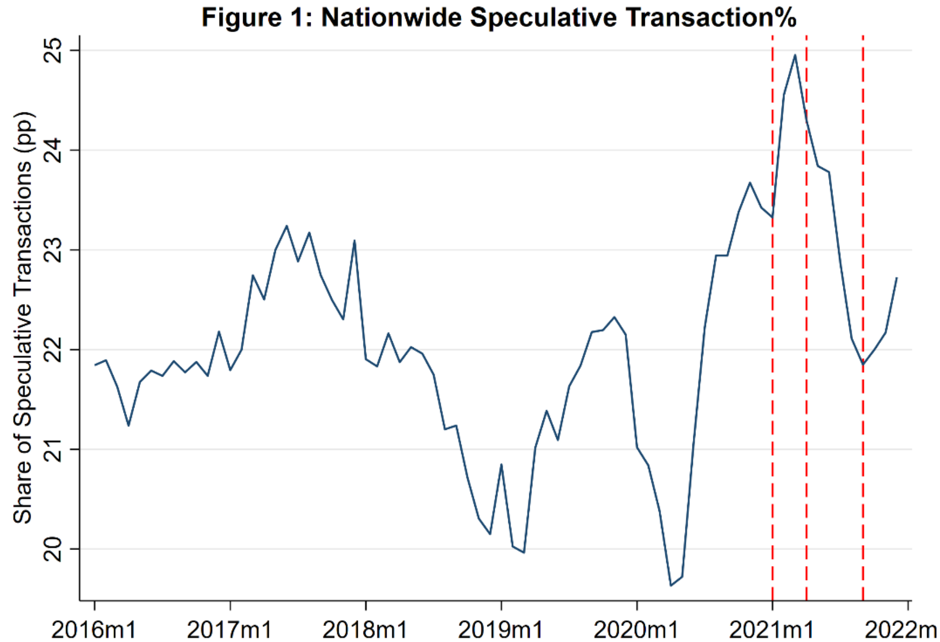


Figure 1. Nationwide Fractions of Speculative Transactions and Corporate Transactions

This figure illustrates the nationwide seasonality adjusted trends of speculative transactions and corporate transactions, respectively, spanning 2016 to 2022 Speculative transactions refer to the purchase of non-owner-occupied houses. To account for seasonal variations in the real estate market, we adjusted the data using monthly seasonality factors calculated 24 months ahead. The three vertical lines indicate the announcement, implementation, and termination of the GSE purchase cap policy, respectively. Data source: CoreLogic.

Figure 2a: Breakdown of GSEs' Mortgage Purchases by Categories

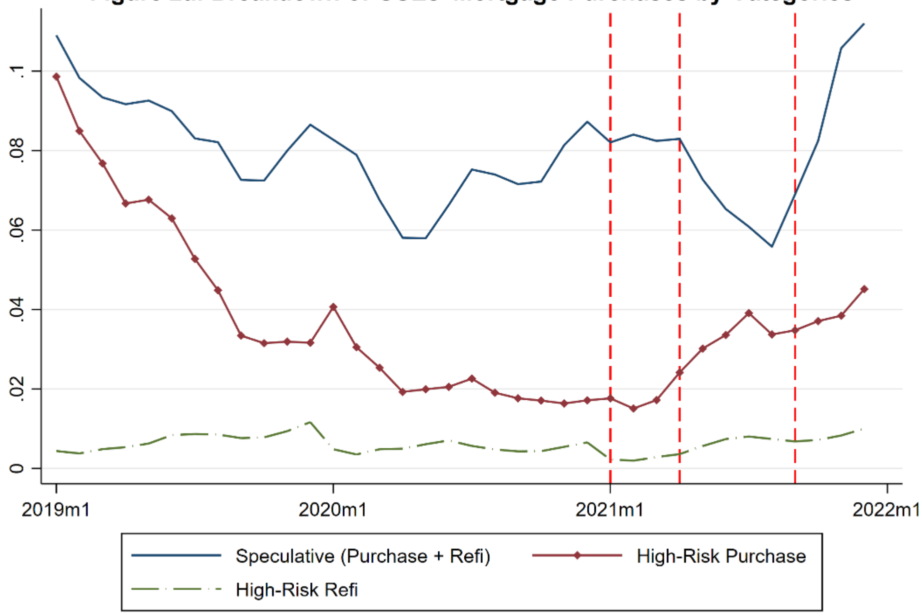
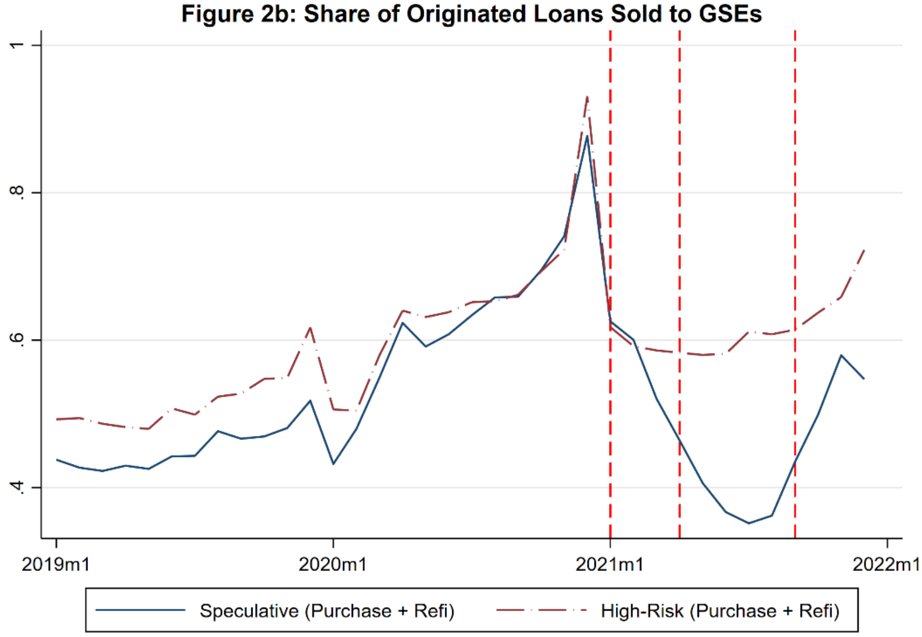


Figure 2b: Share of Originated Loans Sold to GSEs



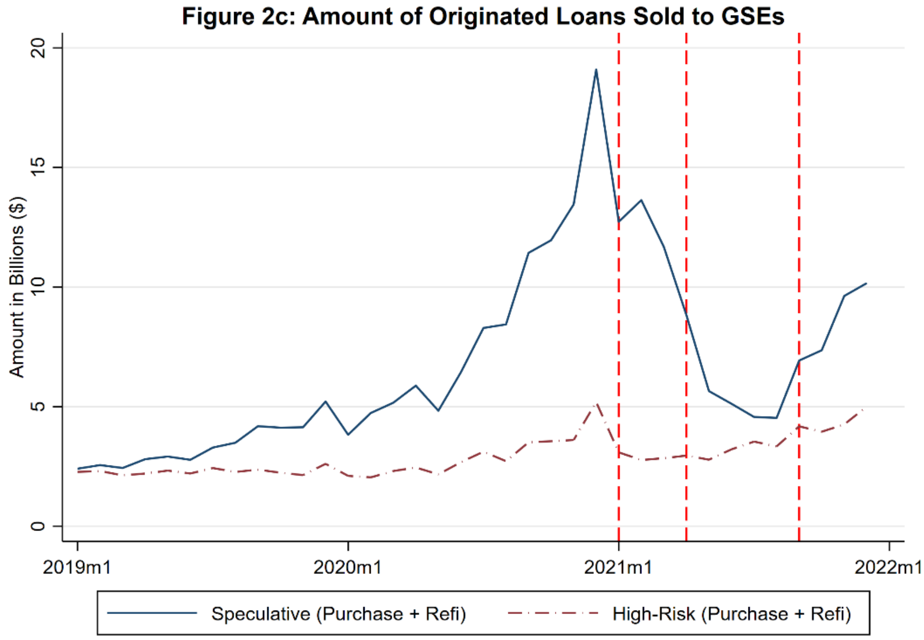


Figure 2c: Amount of Originated Loans Sold to GSEs
Amount in Billions ($)
0
5
10
15
20
2019m1
2020m1
2021m1
2022m1
Speculative (Purchase + Refi)
High-Risk (Purchase + Refi)

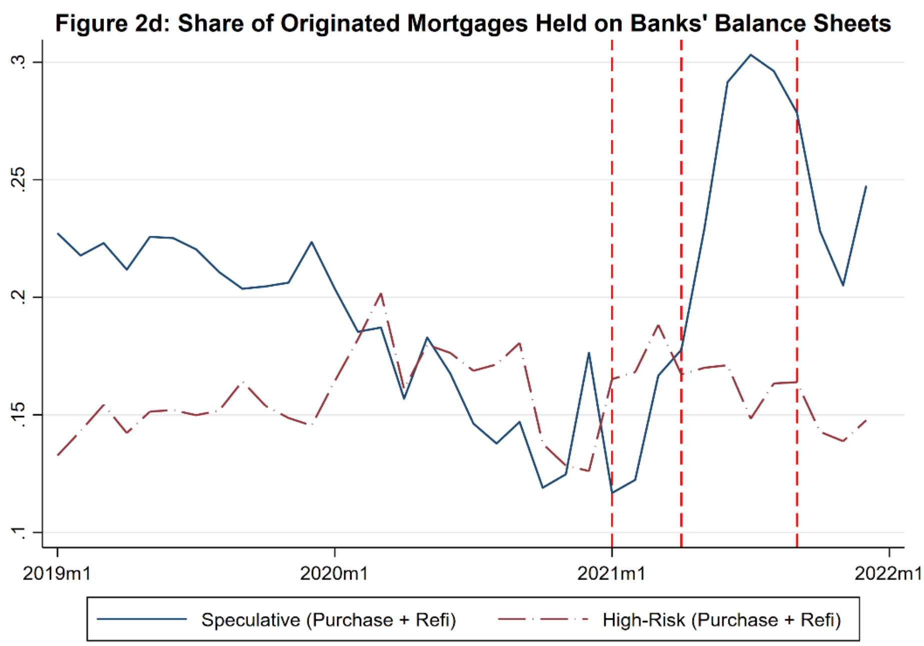


Figure 2d: Share of Originated Mortgages Held on Banks' Balance Sheets
.1
.15
.2
.25
.3
2019m1
2020m1
2021m1
2022m1
Speculative (Purchase + Refi)
High-Risk (Purchase + Refi)

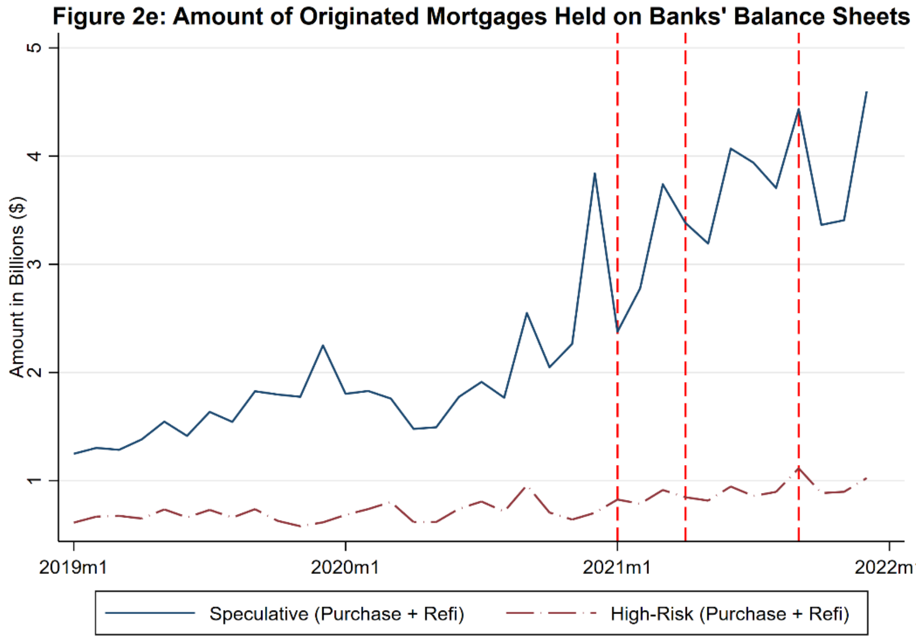
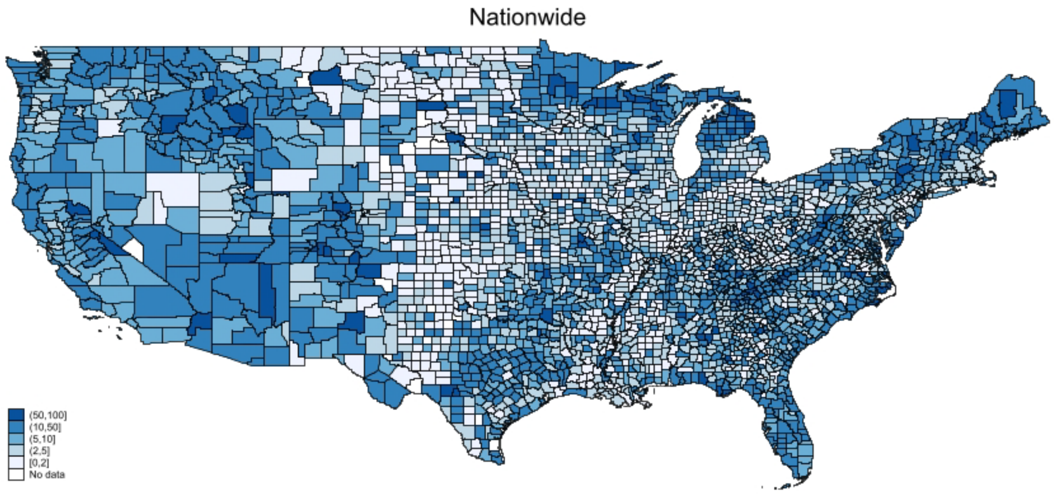


Figure 2. Time Series Plot of CHMDA Mortgage Trends

These figures display nationwide trends in the conforming mortgage loan market. The figures are seasonally adjusted using the 2018 monthly seasonality factors. Figure 2a shows the speculative (purchase and refinance combined), high-risk purchase, and high-risk refinance mortgage loans that are sold to the GSEs as fractions of all mortgage loans sold to the GSEs. Speculative loans refer to mortgage loans that are for second/investment homes. Figure 2b shows the fractions of originated speculative and high-risk mortgage loans sold to the GSEs. Figure 2c shows the amounts of originated speculative and high-risk mortgage loans sold to the GSEs. Figure 2d plots speculative mortgages held on lenders' balance sheets as a fraction of all originated speculative mortgages, as well as the fraction for high-risk mortgages. Figure 2e plots the amounts of speculative mortgages held on lenders' balance sheets and the amounts of high-risk mortgages held on lenders' balance sheets. The three vertical lines in each figure represent the announcement, implementation, and termination of the GSE purchase cap policy, respectively. Data source: Confidential Home Mortgage Disclosure Act (CHMDA).

Panel A: County-level Exposure Nationwide



Panel B: Tract-level Exposure in Major Cities

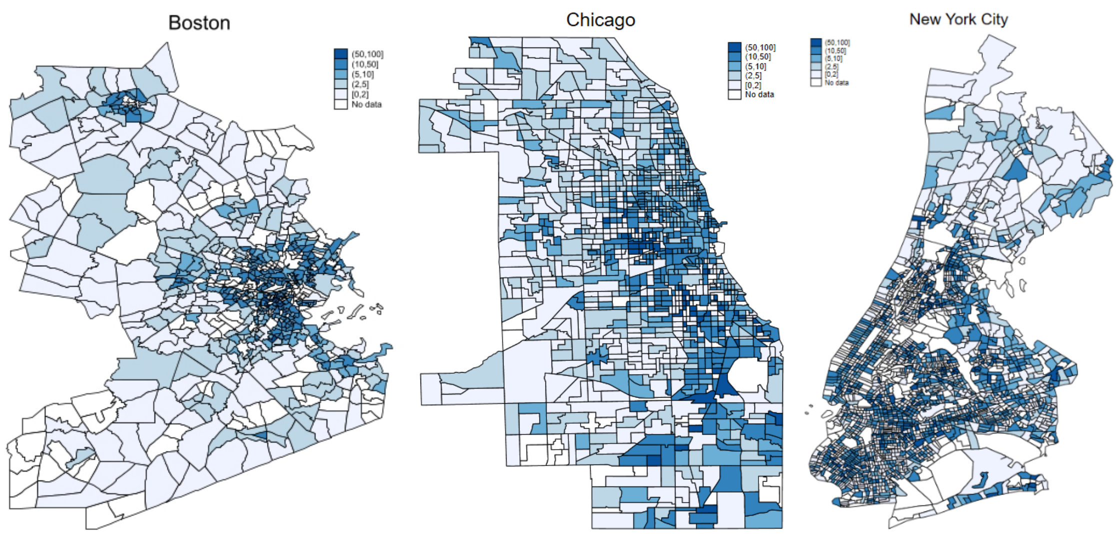


Figure 3. Geographic Exposure to the GSE Purchase Cap Policy

Panel A plots county-level exposure to the GSE purchase cap policy across the United States. County-level exposure to the policy is computed as the percentage of second/investment home–backed mortgages that the GSEs purchased in each county in 2020. Panel B plots tract-level exposure to the policy in three major cities: Boston, Chicago, and New York. Tract-level exposure to the policy is computed as the percentage of second/investment home–backed mortgages that the GSEs purchased in each census tract in 2020. Data source: Confidential Home Mortgage Disclosure Act (CHMDA).

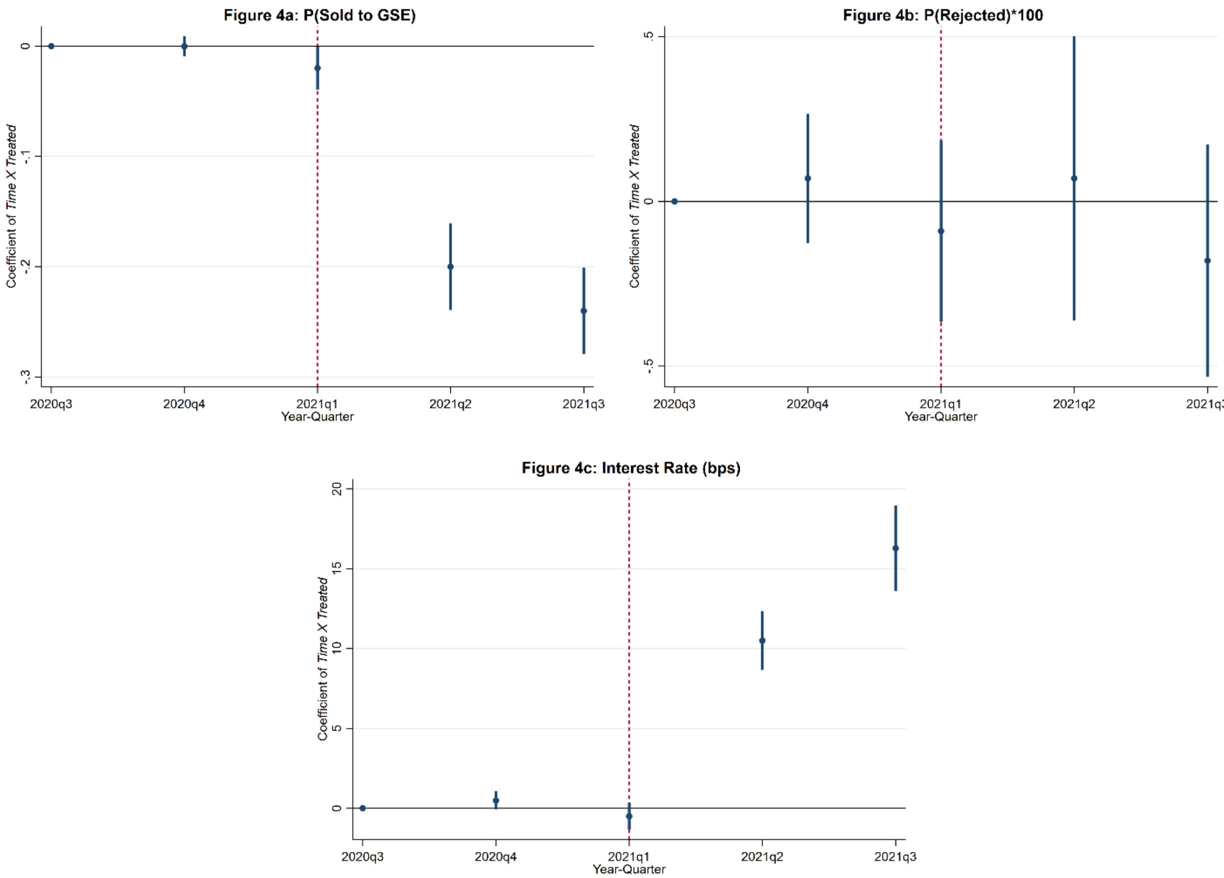


Figure 4. Parallel Trends for Loan-Level CHMDA

Figure 4a plots coefficients and 95 percent confidence intervals from a loan-level OLS regression where the GSE sale indicator variable is regressed onto year-quarter indicator variables interacted with the treatment indicator variable, which equals one for mortgages associated with second/investment homes and zero otherwise. The outcome variable equals one if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. Figure 4b plots coefficients and 95 percent confidence intervals from an application-level OLS regression where the rejection indicator variable, multiplied by 100, is regressed onto year-quarter indicator variables interacted with the treatment indicator variable, which equals one for mortgage applications associated with second/investment homes and zero otherwise. The outcome variable equals 100 if the mortgage application was rejected and zero otherwise. Figure 4c plots coefficients and 95 percent confidence intervals from a loan-level OLS regression where the interest rate, expressed in basis points, is regressed onto year-quarter indicator variables interacted with the treatment indicator variable, which equals one for mortgages associated with second/investment homes and zero otherwise. The regression specification includes control variables outlined in the Internet Appendix, tract fixed effects, and lender by year-quarter fixed effects. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. The sample is composed of speculative and safe conforming home purchase mortgage applications. Heteroskedasticity-robust standard errors are clustered at the lender level. Data source: CHMDA.

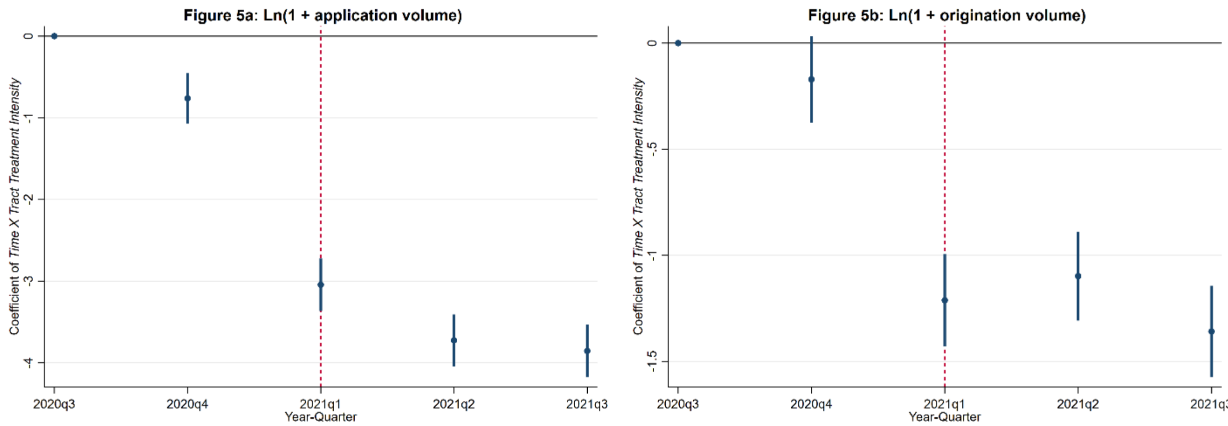


Figure 5. Parallel Trends for Tract-Level CHMDA

Figure 5a plots coefficients and 95 percent confidence intervals from a tract by year-quarter-level OLS regression where the ln(1 + application volume) of second/investment home–backed mortgages is regressed onto year-quarter indicator variables interacted with the tract-level GSE purchase cap policy treatment intensity variable. Figures 5b plots the same specifications but with ln(1 + origination volume) as the outcome variable. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. Heteroskedasticity-robust standard errors are clustered at the tract level. Data source: CHMDA.

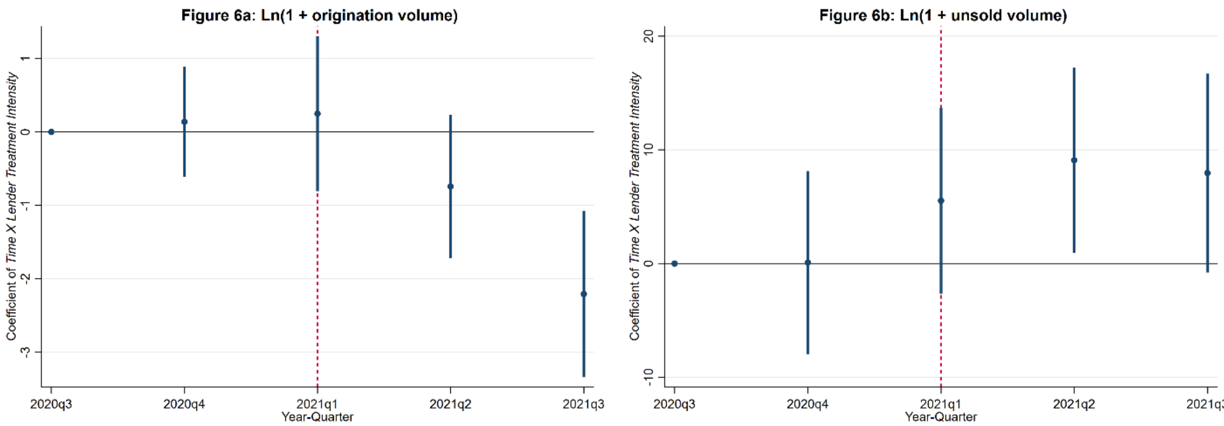


Figure 6. Parallel Trends for Lender-Level CHMDA

Figure 6a plots coefficients and 95 percent confidence intervals from a lender by year-quarter-level OLS regression where the ln(1 + origination volume) of second/investment home–backed mortgages is regressed onto year-quarter indicator variables interacted with the lender-level GSE purchase cap policy treatment intensity variable. Figures 6b plots the same specifications but with ln(1 + unsold volume) as the outcome variable. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. Heteroskedasticity-robust standard errors are clustered at the lender level. Data source: CHMDA.

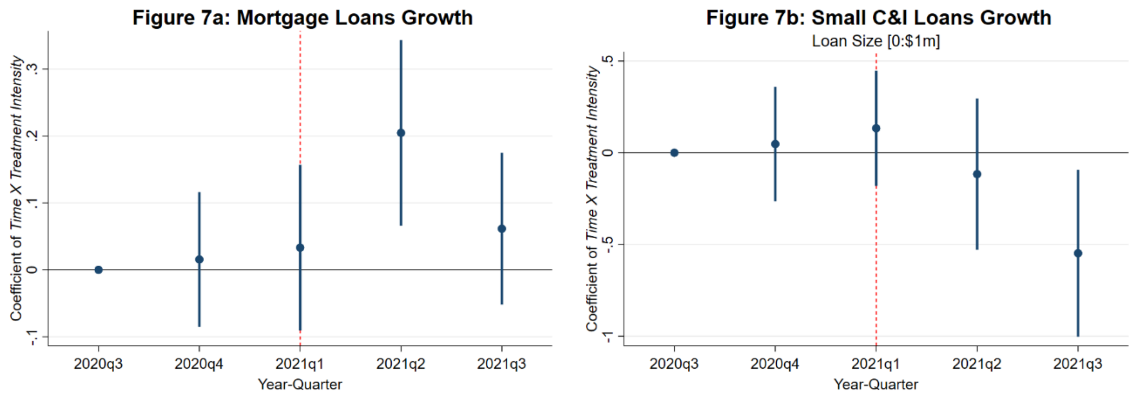


Figure 7. Parallel Trends for Mortgage and C&I Loan Growth

Figure 7a plots coefficients and 95 percent confidence intervals from a bank-quarter-level OLS regression where the growth rate of mortgage loans held on the lender's balance sheet is regressed onto year-quarter indicator variables interacted with lender-level GSE purchase cap policy treatment intensity variable. Treatment intensity is a measure of each lender's exposure to the policy in the pre-period, explained in the main text. Figure 7b plots coefficients and 95 percent confidence intervals from a bank-quarter-level OLS regression where the growth rate of small C&I loans ($1 million or lower) held on the lender's balance sheet is regressed onto year-quarter indicator variables interacted with the lender-level GSE purchase cap policy treatment intensity variable. The regression specification includes control variables outlined in the Internet Appendix, lender fixed effects, and year-quarter fixed effects. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. The sample is composed of lenders with above median total assets in our sample ($809 million). Heteroskedasticity-robust standard errors are clustered at the lender level. Data source: Call Report.

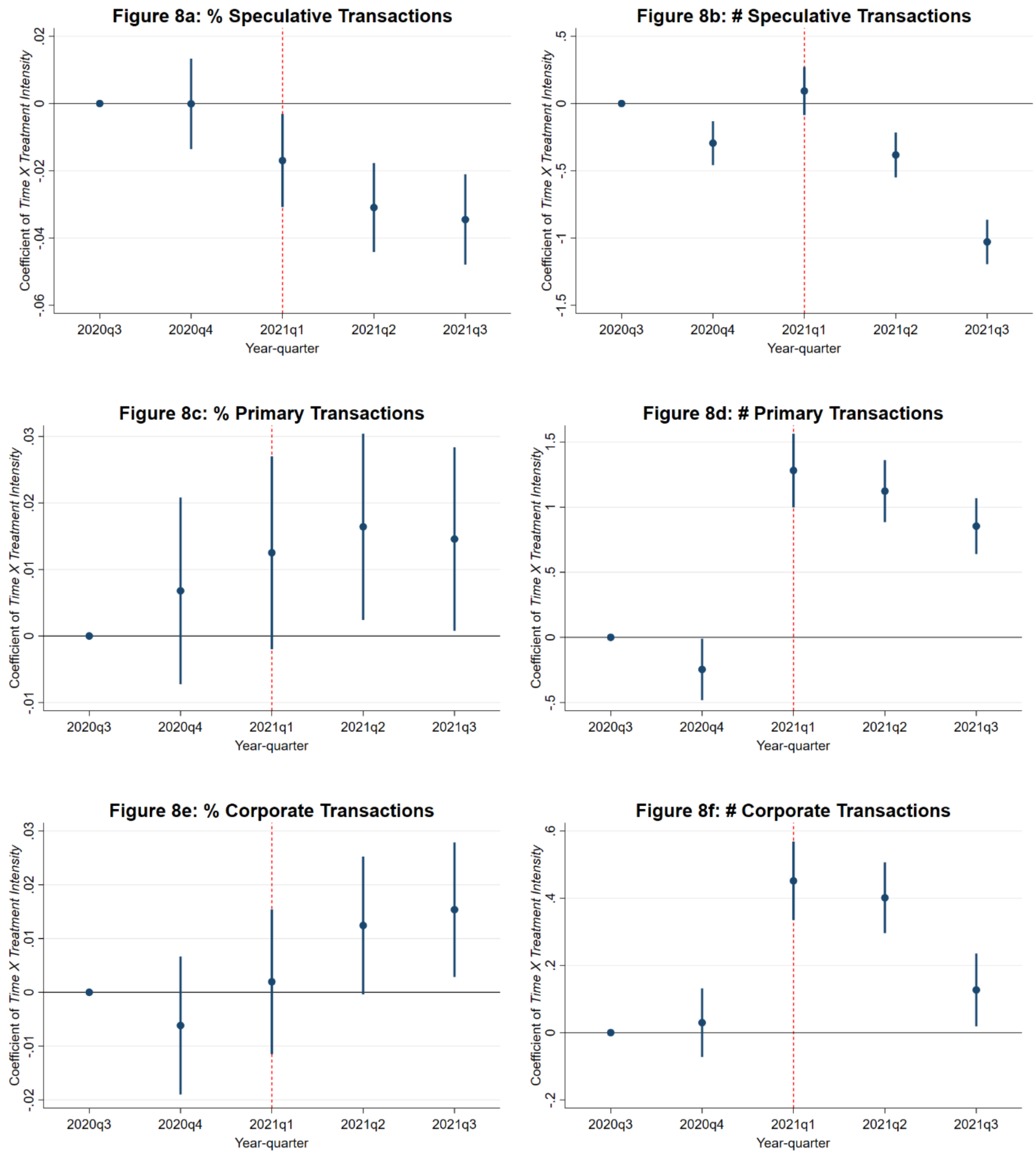


Figure 8. Parallel Trends for House Transactions

Figure 8 plots coefficients and 95 percent confidence intervals from a tract-quarter-level OLS regression where the percentage and the number of speculative, primary, and corporate transactions of single-family houses are separately regressed onto year-quarter indicator variables interacted with the tract-level GSE purchase cap policy treatment intensity variable. The outcome variable for Figure 8a is the percentage of speculative transactions associated with second/investment homes in a given tract and year-quarter. The outcome variable for Figure 8b is the number of speculative transactions associated with second/investment homes in a given tract and year-quarter. The outcome variable for Figure 8c is the percentage of primary transactions associated with primary residences in a given tract and year-quarter. The outcome variable for Figure 8d is the number of primary transactions associated with primary residences in a given tract and year-quarter. The outcome variable for Figure 8e is the percentage of transactions associated with corporate buyers in a given tract and year-quarter. The outcome variable for Figure 8f is the number of transactions associated with corporate buyers in a given tract and year-quarter. Treatment intensity is a measure of each tract's exposure to the policy in the pre-period, explained in the main text. The regression specification includes control variables outlined in the Internet Appendix, tract fixed effects, and year-quarter fixed effects. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. The sample is composed of transactions of single-family houses. Heteroskedasticity-robust standard errors are clustered at the tract level. Data source: CoreLogic.

Table 1. Summary Statistics (CHMDA)

This table presents summary statistics for CHMDA mortgage variables that were used in our empirical analyses. The sample period is from Q3:2020 to Q3:2021. Refer to the Internet Appendix for additional details on variable definitions. Data source: CHMDA.

	Mean	Median	S.D.	N
	(1)	(2)	(3)	(4)
Panel A: Loan level				
Outcome variable				
Rejected	0.06	0.00	0.23	3,748,311
GSE Sale	0.62	1.00	0.48	3,459,418
Interest Rate (bps)	307.07	299.90	37.43	3,457,395
Policy exposure (Loan)				
Second/Investment Home	0.13	0.00	0.34	3,748,311
Risky Mortgage	0.07	0.00	0.26	3,748,311
Panel B: Tract-quarter level				
Application volume (USD millions)				
Speculative home purchase	0.41	0.13	0.78	340,162
Risky home purchase	0.25	0.05	0.39	340,162
Safe home purchase	2.93	1.73	3.48	340,162
Origination volume (USD millions)				
Speculative home purchase	0.61	0.33	0.84	205,236
Risky home purchase	0.19	0.00	0.33	330,512
Safe home purchase	2.81	1.66	3.31	330,512
Policy exposure (Tract)				
Treatment intensity	0.10	0.05	0.15	340,162
Panel C: Lender-quarter level				
Origination volume (USD millions)				
Speculative home purchase	13.03	3.23	34.04	2,377
Risky home purchase	31.78	7.56	77.75	2,387
Safe home purchase	75.98	19.43	189.57	2,410
Speculative refinance	8.02	1.87	20.51	2,311
Risky refinance	0.74	0.19	1.97	1,729
Safe refinance	103.17	21.79	286.82	2,407
Unsold volume (USD millions)				
Speculative home purchase	4.33	0.97	11.73	2,369
Risky home purchase	6.39	1.03	16.92	2,367
Safe home purchase	18.83	3.64	48.12	2,409
Speculative refinance	2.74	0.37	8.69	2,288
Risky refinance	0.19	0.00	0.43	1,182
Safe refinance	26.83	2.25	92.38	2,406
Policy exposure (Lender)				
Treatment intensity	0.08	0.08	0.06	2,697

Table 2. Summary Statistics (CoreLogic and Call Report)

This table presents summary statistics for housing transaction data from CoreLogic and bank data from the Call Report used in our empirical analyses. The sample period is from Q3:2020Q3 to Q3:2021. Data sources: CoreLogic and Call Report.

	Mean	Median	S.D.	N
	(1)	(2)	(3)	(4)
Panel A: Housing transactions (Tract-quarter level)				
Outcome variable				
# Speculative Transactions	3.881	2.015	5.063	329328
# Primary Transactions	12.270	8.526	13.150	329328
# Corporate Transactions	1.708	0.940	2.290	329328
% Speculative Transactions	0.239	0.154	0.260	330,125
% Primary Transactions	0.622	0.697	0.291	330,125
% Corporate Transactions	0.106	0.059	0.152	330,125
Policy exposure (Tract)				
Treatment Intensity	0.107	0.050	0.162	345,490
Panel B: Bank call report (Lender-quarter level)				
Outcome variable				
Mortgage Loan Growth	-0.001	-0.005	0.092	1,790
Small C&I Loan Growth [0:$100k]	-0.106	-0.069	0.297	1,788
Small C&I Loan Growth [$100k:$250k]	-0.090	-0.072	0.271	1,788
Small C&I Loan Growth [$250k:$1m]	-0.080	-0.068	0.227	1,788
Small C&I Loan Growth [0:$1m]	-0.088	-0.068	0.213	1,788
Policy exposure (Lender)				
Treatment Intensity	0.092	0.078	0.079	1,790
Lender characteristics				
ROE	0.060	0.054	0.069	1,790
Capital Ratio	0.108	0.104	0.023	1,790
Deposit/Assets	0.831	0.843	0.054	1,790
Ln(Assets)	15.021	14.742	1.033	1,790
Total Assets (USD)	6,370,849	2,525,130	9,729,763	1,790
Assets Growth	0.023	0.019	0.049	1,790

Table 3. GSE Purchase Cap Policy and GSE Sale Probability

This table presents loan-level OLS regression results where the GSE sale indicator variable is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. In Panel A, Speculative equals one for mortgages associated with second/investment homes and zero for safe mortgages associated with primary residences. In Panel B, Risky equals one for risky mortgages associated with primary residences and zero for safe mortgages associated with primary residences. Refer to the main text for details on the definition of "risky." Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. The sample includes conforming home purchase mortgages that were originated between Q3:2020 and Q3:2021. Refer to the main text for details on the sample construction process. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

Panel A: Speculative versus Safe

	P(GSE Sale)*100		
	(1)	(2)	(3)
Speculative	3.07***	1.28**	0.57*
	[0.79]	[0.64]	[0.34]
Speculative x Announcement	-2.53***	-2.13***	-2.25***
	[0.78]	[0.78]	[0.77]
Speculative x Implementation	-20.02***	-18.95***	-21.81***
	[1.79]	[1.76]	[1.92]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,241,985	3,240,649	3,240,086
R-squared	0.07	0.13	0.59

Panel B: Risky versus Safe

	P(GSE Sale)*100		
	(1)	(2)	(3)
Risky	-0.14	0.50	0.31
	[0.92]	[1.00]	[0.39]
Risky x Announcement	0.68	0.62	0.52
	[0.55]	[0.51]	[0.39]
Risky x Implementation	0.41	0.68	0.61
	[0.71]	[0.52]	[0.47]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,004,586	3,002,715	3,002,164
R-squared	0.07	0.14	0.61

Table 4. GSE Purchase Cap Policy and Home Purchase Mortgage Application Rejection

This table presents application-level OLS regression results where the application rejection indicator is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable equals 100 if the mortgage application was rejected and zero otherwise. In Panel A, Speculative equals one for mortgage applications associated with second/investment homes and zero for safe mortgage applications associated with primary residences. In Panel B, Risky equals one for risky mortgage applications associated with primary residences and zero for safe mortgage applications associated with primary residences. Refer to the main text for details on the definition of "risky." Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. The sample includes conforming home purchase mortgage applications where the approval/rejection decision was made between Q3:2020 and Q3:2021. Refer to the main text for details on the sample construction process. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

Panel A: Speculative versus Safe

	P(Rejected)*100		
	(1)	(2)	(3)
Speculative	2.08***	1.33***	1.30***
	[0.14]	[0.13]	[0.11]
Speculative x Announcement	-0.30**	-0.28**	-0.12
	[0.15]	[0.12]	[0.13]
Speculative x Implementation	0.26	-0.25	-0.09
	[0.02]	[0.02]	[0.02]
Mean of Outcome Variable	4.54	4.54	4.54
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,474,271	3,472,708	3,472,141
R-squared	0.04	0.24	0.29

Panel B: Risky versus Safe

	P(Rejected)*100		
	(1)	(2)	(3)
Risky	14.96***	3.10***	2.35***
	[0.98]	[0.28]	[0.21]
Risky x Announcement	1.36***	0.36**	0.18
	[0.38]	[0.18]	[0.17]
Risky x Implementation	-2.87***	-2.34***	-2.05***
	[0.36]	[0.31]	[0.25]
Mean of Outcome Variable	5.34	5.34	5.34
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y

SE Cluster	Lender	Lender	Lender
Observations	3,245,339	3,243,605	3,243,031
R-squared	0.07	0.34	0.39

Table 5. GSE Purchase Cap Policy and Interest Rate

This table presents mortgage-level OLS regression results where the interest rate is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable is the interest rate of the mortgage at origination, expressed in basis points. In Panel A, Speculative equals one for mortgages associated with second/investment homes and zero for safe mortgages associated with primary residences. In Panel B, Risky equals one for risky mortgages associated with primary residences and zero for safe mortgages associated with primary residences. Refer to the main text for details on the definition of “risky.” Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. The sample includes conforming home purchase mortgages that were originated between Q3:2020 and Q3:2021. Refer to the main text for details on the sample construction process. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

Panel A: Speculative versus Safe

	Interest Rate (bps)		
	(1)	(2)	(3)
Speculative	27.65***	25.84***	26.31***
	[0.75]	[0.70]	[0.70]
Speculative x Announcement	-0.42	-0.70*	-0.75*
	[0.45]	[0.39]	[0.41]
Speculative x Implementation	13.33***	12.78***	13.02***
	[1.36]	[1.19]	[1.02]
Mean of Outcome Variable	306.21	306.21	306.21
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,240,223	3,238,883	3,238,316
R-squared	0.28	0.43	0.54

Panel B: Risky versus Safe

	Interest Rate (bps)		
	(1)	(2)	(3)
Risky	15.17***	-0.24	-0.02
	[1.55]	[0.73]	[0.62]
Risky x Announcement	-1.73***	-1.62***	-1.15***
	[0.48]	[0.45]	[0.39]
Risky x Implementation	-0.51	-1.16*	-0.73
	[0.86]	[0.68]	[0.61]
Mean of Outcome Variable	303.01	303.01	303.01
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,002,956	3,001,078	3,000,527

R-squared	0.21	0.42	0.55

Table 6. GSE Purchase Cap Policy and Tract Home Purchase Mortgage Supply

This table presents OLS regression results where log origination volume, measured in nominal U.S. dollars, is regressed onto GSE purchase cap policy treatment intensity variables. Each observation is a census tract by year-quarter. The outcome variable for columns 1 and 2 is the natural log of one plus the total amount, in nominal U.S. dollars, of conforming home purchase mortgages associated with second/investment homes that were originated in a given tract and year-quarter. The outcome variable for columns 3 and 4 is the natural log of one plus the total amount, in nominal U.S. dollars, of risky conforming home purchase mortgages associated with primary residences that were originated in a given tract and year-quarter. Refer to the main text for details on the definition of "risky." The outcome variable for columns 5 and 6 is the natural log of one plus the total amount, in nominal U.S. dollars, of safe conforming home purchase mortgages associated with primary residences that were originated in a given tract and year-quarter. Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. Treatment intensity is a measure of each tract's exposure to the policy in the pre-period, explained in the main text. The application pool characteristic control variables are constructed for the respective loan category (speculative, risky, or safe). Refer to the main text for details on sample construction. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

	Ln(1 + Origination Volume)					
	Speculative		Risky		Safe	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Intensity x Announcement	-1.305***	-1.124***	0.859***	0.840***	0.590***	0.495***
	[0.101]	[0.095]	[0.312]	[0.322]	[0.092]	[0.083]
Treatment Intensity x Implementation	-1.413***	-1.140***	0.546**	0.549**	0.521***	0.434***
	[0.081]	[0.075]	[0.236]	[0.244]	[0.072]	[0.065]
Median Credit Score 1 = 100		0.543***		0.197***		0.280***
		[0.030]		[0.070]		[0.018]
Median CLTV 1 = 100%		0.398***		-0.479**		1.012***
		[0.117]		[0.242]		[0.066]
Median DTI 1 = 100%		-3.219***		-0.265		-0.167*
		[0.126]		[0.342]		[0.092]
Median Income 1 = 100K		-0.048***		-0.074		-0.101***
		[0.008]		[0.073]		[0.021]
Median Loan Amount 1 = 100K		0.450***		0.087**		0.383***
		[0.012]		[0.035]		[0.010]
Asian Share 1 = 100%		0.013		0.17		0.052
		[0.035]		[0.157]		[0.042]
Black Share 1 = 100%		-0.361***		0.029		-0.134***
		[0.061]		[0.149]		[0.047]
Hispanic Share 1 = 100%		-0.072*		-0.372***		-0.036
		[0.041]		[0.115]		[0.035]
Female Share 1 = 100%		0.053*		0.056		0.081***
		[0.027]		[0.087]		[0.023]
Median Age		-0.003***		0.001		-0.007***
		[0.001]		[0.002]		[0.001]
Two-Borrowers Share 1 = 100%		0.199***		-0.015		0.094***
		[0.027]		[0.096]		[0.025]

S.D. of Treatment Intensity	0.16	0.16	0.12	0.12	0.14	0.14
Tract FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
SE Cluster	Tract	Tract	Tract	Tract	Tract	Tract
Observations	194,838	184,005	172,331	168,585	329,475	325,791
R-squared	0.443	0.464	0.418	0.411	0.599	0.632

Table 7. GSE Purchase Cap Policy and Tract Home Purchase Mortgage Application Volume

This table presents OLS regression results where log application volume, in nominal U.S. dollars, is regressed onto GSE purchase cap policy treatment intensity variables. Each observation is a census tract by year-quarter. The outcome variable for column 1 is the natural log of one plus the total amount, in nominal U.S. dollars, of conforming home purchase mortgage applications associated with second/investment homes in a given tract and year-quarter. The outcome variable for column 2 is the natural log of one plus the total amount, in nominal U.S. dollars, of risky conforming home purchase mortgage applications associated with primary residences in a given tract and year-quarter. Refer to the main text for details on the definition of "risky." The outcome variable for column 3 is the natural log of one plus the total amount, in nominal U.S. dollars, of safe conforming home purchase mortgage applications associated with primary residences in a given tract and year-quarter. Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. Treatment intensity is a measure of each tract's exposure to the policy in the pre-period, explained in the main text. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

	Ln(1 + Application Volume)		
	Speculative	Risky	Safe
	(1)	(2)	(3)
Treatment Intensity x Announcement	-2.661***	1.378***	0.698***
	[0.141]	[0.166]	[0.120]
Implement x Treatment Intensity	-3.406***	0.393***	0.995***
	[0.116]	[0.137]	[0.095]
S.D. of Treatment Intensity	0.15	0.15	0.15
Tract FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
SE Cluster	Tract	Tract	Tract
Observations	339,607	339,607	339,607
R-squared	0.458	0.432	0.589

Table 8. GSE Purchase Cap Policy and Home Purchase Mortgages Held on Balance Sheet

This table presents OLS regression results where log unsold volume, in nominal U.S. dollars, is regressed onto GSE purchase cap policy treatment intensity variables. Each observation is a bank by year-quarter. The outcome variable for column 1 is the natural log of one plus the total amount, in nominal U.S. dollars, of conforming home purchase mortgages associated with second/investment homes that were originated and held by a given bank and year-quarter. The outcome variable for column 2 is the natural log of one plus the total amount, in nominal U.S. dollars, of risky conforming home purchase mortgages associated with primary residences that were originated and held by a given bank and year-quarter. Refer to the main text for details on the definition of "risky." The outcome variable for column 3 is the natural log of the total amount, in nominal U.S. dollars, of safe conforming home purchase mortgages associated with primary residences that were originated and held by a given bank and year-quarter. The outcome variable for column 4 is the natural log of the total amount, in nominal U.S. dollars, of jumbo home purchase mortgages associated with primary residences that were originated and held in a given bank and year-quarter. Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. Treatment intensity is a measure of each bank's exposure to the policy in the pre-period, explained in the main text. The application pool characteristic control variables are constructed for the respective loan category (speculative, risky, or safe). Refer to the main text for details on sample construction. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the bank level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

	Ln(1 + Unsold Balance)			
	Speculative	Risky	Safe	Jumbo
	(1)	(2)	(3)	(4)
Treatment Intensity x Announcement	5.491	-1.568	-0.269	0.806
	[3.468]	[4.942]	[3.110]	[1.507]
Treatment Intensity x Implementation	8.491***	4.337	1.156	3.196
	[3.115]	[3.234]	[2.267]	[2.607]
ROE	3.883	4.009	0.447	0.784
	[2.664]	[2.454]	[1.769]	[3.258]
Capital Ratio	7.144	-3.493	-10.222	-7.683
	[15.408]	[15.640]	[9.771]	[23.301]
Deposit Ratio	-3.700	-9.506**	-2.372	1.131
	[4.198]	[4.475]	[2.770]	[5.767]
Ln(Total Assets)	-0.613	-0.077	-0.542	0.669
	[1.434]	[1.412]	[0.883]	[0.804]
Median Credit Score 1 = 100	-0.787	-0.174	0.054	0.434
	[0.615]	[0.364]	[0.793]	[0.307]
Median CLTV 1 = 100%	1.640	1.978	0.365	1.052
	[2.679]	[3.638]	[2.601]	[1.323]
Median DTI 1 = 100%	-2.177	2.295	5.572	1.850*
	[2.098]	[1.477]	[4.639]	[0.948]
Median Income 1 = 100K	-0.310	0.273	0.637	0.048
	[0.266]	[0.533]	[0.972]	[0.042]
Median Loan Amount 1 = 100K	-0.193	0.005	-0.463	0.128***
	[0.259]	[0.170]	[0.376]	[0.036]
Asian Share 1 = 100%	-0.115	-1.141	-1.183	-0.171
	[1.294]	[1.046]	[3.166]	[0.369]
Black Share 1 = 100%	0.010	-0.448	-1.107	1.010
	[2.351]	[0.986]	[2.893]	[0.907]
Hispanic Share 1 = 100%	-1.514*	0.753	-1.382	-0.237
	[0.818]	[0.477]	[1.231]	[0.429]

Female Share 1 = 100%	0.837	-0.513	2.715	1.406
	[1.776]	[0.853]	[1.977]	[1.217]
Two-Borrowers Share 1 = 100%	1.199	-1.438***	1.553	-0.042
	[0.819]	[0.538]	[1.391]	[0.443]
Median Age	0.015	0.026*	0.013	0.012
	[0.019]	[0.015]	[0.022]	[0.011]
S.D. of Treatment Intensity	0.06	0.09	0.09	0.05
Lender FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
SE Cluster	Lender	Lender	Lender	Lender
Observations	2339	2125	2404	1758
R-squared	0.660	0.685	0.977	0.782

Table 9. GSE Purchase Cap Policy, Mortgages, and C&I Loans

This table presents OLS regression results where the growth rates, constructed as log differences, of mortgage loans and small C&I loans held on the lender's balance sheet are separately regressed onto GSE purchase cap policy treatment intensity variables. The sample only includes lenders with above median total assets in our sample (>$809 million). Each observation is a lender by year-quarter. The outcome variable for columns 1 and 2 is the growth rate of mortgage loans held on the lender's balance sheet in a given year-quarter. The outcome variable for columns 3 and 4 is the growth rate of small C&I loans ($1 million or lower) held on the lender's balance sheet in a given year-quarter. The outcome variable for columns 5 and 6 is the growth rate of new jumbo mortgage loans held on the lender's balance sheet in a given year-quarter. Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. Treatment intensity is a measure of each lender's exposure to the policy in the pre-period, explained in the main text. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data sources: Call Report and CHMDA.

	Mortgage Loan Growth		C&I Loan Growth [0:$1m]		Jumbo Loan Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement x Treatment Intensity		0.028		0.104		6.024
		[0.060]		[0.169]		[8.966]
Implementation x Treatment Intensity	0.120**	0.129***	-0.395**	-0.360*	4.314	6.343**
	[0.047]	[0.044]	[0.178]	[0.199]	[3.016]	[3.023]
Ln(Assets)	-0.263*	-0.264*	-0.305	-0.307	0.911	0.755
	[0.151]	[0.151]	[0.270]	[0.271]	[2.308]	[2.295]
Assets Growth	0.637***	0.638***	0.260	0.263	-1.352	-1.08
	[0.149]	[0.149]	[0.210]	[0.209]	[5.589]	[5.628]
ROE	0.044	0.044	-0.137	-0.137	-3.116	-3.133
	[0.037]	[0.037]	[0.114]	[0.114]	[5.219]	[5.211]
Capital Ratio	-2.880***	-2.886***	-0.511	-0.532	44.515	43.112
	[0.751]	[0.749]	[1.588]	[1.586]	[33.163]	[33.225]
Deposit/Assets	-0.029	-0.032	-0.310	-0.320	-7.812	-8.385
	[0.266]	[0.269]	[0.433]	[0.435]	[10.716]	[10.478]
S.D. of Treatment Intensity	0.079	0.079	0.078	0.078	0.080	0.080
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y
Cluster	Lender	Lender	Lender	Lender	Lender	Lender
Observations	1,790	1,790	1,788	1,788	1780	1780
R-squared	0.353	0.353	0.309	0.309	0.084	0.085

Table 10. GSE Purchase Cap Policy and Small Business Loan Growth

This table presents OLS regression results where the growth rates, constructed as log differences, of small C&I loans held on the lender's balance sheet are separately regressed onto GSE purchase cap policy treatment intensity variables. Lenders with above median total assets in our sample (> 809 million USD) are used in this table. Each observation is a lender by year-quarter. The outcome variable for columns 1 and 2 is the growth rate of small C&I loans ($100,000 or lower) held on the lender's balance sheet in a given year-quarter. The outcome variable for columns 3 and 4 is the growth rate of small C&I loans (between $100,000 and $250,000) held on the lender's balance sheet in a given year-quarter. The outcome variable for columns 5 and 6 is the growth rate of small C&I loans (between $250,000 and $1 million) held on the lender's balance sheet in a given year-quarter. Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. Treatment intensity is a measure of each lender's exposure to the policy in the pre-period, explained in the main text. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: Call Report.

	Small C&I Loan Growth					
	[0:$100k]		[$100k:$250k]		[$250k:$1m]	
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement x Treatment Intensity		-0.033		0.157		0.211
		[0.193]		[0.189]		[0.183]
Implementation x Treatment Intensity	-0.399**	-0.410**	-0.403**	-0.350	-0.512***	-0.441**
	[0.169]	[0.204]	[0.205]	[0.228]	[0.180]	[0.220]
Ln(Assets)	-0.187	-0.187	-0.478	-0.481	-0.030	-0.035
	[0.408]	[0.411]	[0.345]	[0.347]	[0.175]	[0.177]
Assets Growth	0.138	0.138	0.010	0.014	0.428***	0.434***
	[0.380]	[0.378]	[0.314]	[0.313]	[0.163]	[0.162]
ROE	-0.160	-0.160	-0.184*	-0.184*	-0.240**	-0.240**
	[0.132]	[0.132]	[0.098]	[0.098]	[0.114]	[0.114]
Capital Ratio	3.349	3.356	-0.059	-0.090	0.006	-0.035
	[2.440]	[2.438]	[1.266]	[1.263]	[1.385]	[1.376]
Deposit/Assets	-1.523**	-1.520**	-0.610	-0.625	0.469	0.449
	[0.628]	[0.630]	[0.528]	[0.529]	[0.483]	[0.486]
S.D. of Treatment Intensity	0.078	0.078	0.078	0.078	0.078	0.078
Lender FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
SE Cluster	Lender	Lender	Lender	Lender	Lender	Lender
Observations	1,788	1,788	1,788	1,788	1,788	1,788
R-squared	0.304	0.304	0.291	0.291	0.296	0.297

Table 11. Spillover Effects on CRA Lending

This table presents OLS regression results at the county-lender-year level, where the outcome variable, the log of one plus the lenders' CRA lending, is regressed onto the log of one plus the lenders' speculative loans sold to the GSEs in 2020. We use the 2021 indicator variable to identify the policy's treatment period. The sample includes lender-county pairs that have non-zero CRA lending during 2019–2021 and those that originated and sold some speculative loans to GSEs in 2020, the treatment exposure. Columns 1 and 2 report the results for the 2019–2021 sample, while columns 3 and 4 report the results for the 2020–2021 sample. Heteroskedasticity-robust standard errors are double clustered at both the lender level and the county level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data sources: CRA, CHMDA.

	(1) Ln(CRA Lending + 1)	(2) Ln(CRA Lending + 1)	(3) Ln(CRA Lending + 1)	(4) Ln(CRA Lending + 1)
Ln(2020 Speculative Mortgages Sold to GSEs + 1)	0.987***		0.986***	
	[0.052]		[0.047]	
2021 * Ln(2020 Speculative Mortgages Sold to GSEs + 1)	-0.078***	-0.078***	-0.076**	-0.076**
	[0.030]	[0.030]	[0.031]	[0.031]
S.D. of Treatment Intensity	1.29	1.29	1.29	1.29
Lender-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Lender-County FE		Y		Y
Sample	2019–2021	2019–2021	2020–2021	2020–2021
Cluster	County and Lender	County and Lender	County and Lender	County and Lender
Observations	46,065	46,065	30,710	30,710
R-squared	0.577	0.896	0.585	0.927

Table 12. Spillover Effects on Jumbo Mortgage Lending

This table presents OLS regression results at the county-lender-year level, where the outcome variable, the log of one plus the lenders' jumbo mortgage origination, is regressed onto the log of one plus the lenders' speculative loans sold to GSEs in 2020. We use the 2021 indicator variable to identify the policy's treatment period. The sample includes lender-county pairs that have non-zero jumbo mortgage lending during 2019–2021 and those that originated and sold some speculative loans to GSEs in 2020, the treatment exposure. Columns 1 and 2 report the results for the 2019–2021 sample, while columns 3 and 4 report the results for the 2020–2021 sample. Heteroskedasticity-robust standard errors are double clustered at both the lender level and the county level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

	(1) Ln(Jumbo Originations + 1)	(2) Ln(Jumbo Originations + 1)	(3) Ln(Jumbo Originations + 1)	(4) Ln(Jumbo Originations + 1)
Ln(2020 Speculative Mortgages Sold to GSEs + 1)	1.881***		1.865***	
	[0.050]		[0.053]	
2021 * Ln(2020 Speculative Mortgages Sold to GSEs + 1)	-0.564***	-0.564***	-0.549***	-0.549***
	[0.065]	[0.065]	[0.068]	[0.068]
S.D. of Treatment Intensity	1.38	1.38	1.38	1.38
Lender-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Lender-County FE		Y		Y
Sample	2019–2021	2019–2021	2020–2021	2020–2021
Cluster	County and Lender	County and Lender	County and Lender	County and Lender
Observations	89,160	89,160	59,440	59,440
R-squared	0.426	0.613	0.422	0.693

Table 13. GSE Purchase Cap Policy and Housing Transactions

This table presents OLS regression results where the percentage of speculative, primary, and corporate transactions of single-family houses are separately regressed onto GSE purchase cap policy treatment intensity variables. Each observation is a census tract by year-quarter. The outcome variable for columns 1 and 2 in Panel A is the percentage of speculative transactions, defined as those associated with second/investment home transactions in a given tract and year-quarter. The outcome variable for columns 3 and 4 in Panel A is the percentage of primary residence transactions in a given tract and year-quarter. The outcome variable for columns 5 and 6 in Panel A is the percentage of transactions associated with corporate buyers in a given tract and year-quarter. Panel B reports the results for number of transactions. Panel C reports the results for log of one plus the number of transactions. Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. Treatment intensity is a measure of each tract's exposure to the policy in the pre-period, explained in the main text. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CoreLogic.

Panel A: % Transactions

	% Speculative Transactions		% Primary Transactions		% Corporate Transactions	
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement x Treatment Intensity		-0.017***		0.009		0.005
		[0.006]		[0.007]		[0.006]
Implementation x Treatment Intensity	-0.027***	-0.033***	0.009**	0.012**	0.015***	0.017***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]	[0.005]
Mean of Outcome Variable	0.238	0.238	0.627	0.627	0.104	0.104
S.D. of Treatment Intensity	0.155	0.155	0.155	0.155	0.155	0.155
Tract FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
SE Cluster	Tract	Tract	Tract	Tract	Tract	Tract
Observations	325,155	325,155	325,155	325,155	325,155	325,155
R-squared	0.760	0.760	0.756	0.756	0.493	0.493

Panel B: # Transactions						
	# Speculative Transactions		# Primary Transactions		# Corporate Transactions	
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement x Treatment Intensity		0.241***		1.404***		0.437***
		[0.083]		[0.136]		[0.054]
Implementation x Treatment Intensity	-0.638***	-0.558***	0.644***	1.112***	0.104***	0.250***
	[0.060]	[0.068]	[0.085]	[0.094]	[0.038]	[0.041]
Mean of Outcome Variable	3.920	3.921	12.439	12.439	1.720	1.720
S.D. of Treatment Intensity	0.155	0.155	0.155	0.155	0.155	0.155
Tract FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
SE Cluster	Tract	Tract	Tract	Tract	Tract	Tract
Observations	324,375	324,375	324,375	324,375	324,375	324,375
R-squared	0.850	0.850	0.904	0.904	0.690	0.690

Panel C: Ln(1 + #Transactions)						
	Ln(1 + # Speculative Transactions)		Ln(1 + # Primary Transactions)		Ln(1 + # Corporate Transactions)	
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement x Treatment Intensity		0.044***		0.136***		0.095***
		[0.016]		[0.016]		[0.017]
Implementation x Treatment Intensity	-0.111***	-0.096***	0.007	0.052***	0.006	0.038***
	[0.011]	[0.012]	[0.010]	[0.011]	[0.012]	[0.012]
S.D. of Treatment Intensity	0.155	0.155	0.155	0.155	0.155	0.155
Tract FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
SE Cluster	Tract	Tract	Tract	Tract	Tract	Tract
Observations	324,375	324,375	324,375	324,375	324,375	324,375
R-squared	0.790	0.790	0.888	0.888	0.638	0.638

Table 14. Real Effects – Building Permit and Construction Employment

This table presents OLS regression results testing the real effects of the GSE purchase cap policy. Columns 1 and 2 report the results of single-family house building permits. Columns 3 to 6 report the results for residential construction employment and wages. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the county level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data sources: U.S. Census Bureau Building Permits Survey, U.S. Bureau of Labor Statistics, and U.S. Bureau of Economic Analysis.

	Ln(1 + One Unit Permits)		Ln(1 + Construction Employment)		Ln(1 + Avg Construction Workers' Wages)	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Effective Period * County-Level Treatment Intensity	0.21	0.21	0.01	-0.00	0.03	0.03
	[0.15]	[0.16]	[0.02]	[0.02]	[0.02]	[0.02]
Unemployment Rate		-0.01		-0.01**		-0.00
		[0.02]		[0.00]		[0.00]
GDP Growth		-0.00		-0.00		-0.00
		[0.00]		[0.00]		[0.00]
Ln(Per Capita Income)		0.54		0.05		0.07
		[1.24]		[0.19]		[0.16]
S.D. of Treatment Intensity	0.10	0.10	0.13	0.13	0.13	0.13
Year-Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
SE Cluster	County	County	County	County	County	County
Observations	2,939	2,939	8,595	8,595	8,595	8,595
R-squared	0.95	0.95	1.00	1.00	0.92	0.92

Internet Appendix

Loan-Level Control Variables (Confidential Home Mortgage Disclosure Act [CHMDA])

The choice of loan-level control variables and their definitions largely follows Bhutta, Fuster, and Hizmo (2020). Credit score, combined loan-to-value (CLTV) ratio, and debt-to-income (DTI) ratio indicator variables are interacted to form a credit score-CLTV-DTI grid.

Loan Amount Indicator Variables – Applications are sorted into groups according to their loan amounts. The reference group is made up of applications with loan amounts between zero and $50,000. The remaining groups are formed by $50,000 increments up to loan amounts of $749,999. The final group is made up of loans with loan amounts greater than $749,999.

Income Indicator Variables – Applications are sorted into groups according to the applicant's annual income. The reference group is made up of applications with income values between zero and $50,000. The remaining groups are formed by $25,000 increments up to income values of $499,999. The final group is made up of loans associated with applicants with income values greater than $499,999. Loans that have missing income values form a separate group.

CLTV Indicator Variables – Applications are sorted into groups according to the loan's CLTV value. CLTV values from zero to 29 form one group. CLTV values from 30 to 79 form 10-point groups. CLTV values from 80 to 94 form 5-point groups. CLTV values from 95 to 100 form 1-point groups. CLTV values from 101 to 110 form one group. CLTV values from 111 to 120 form one group. CLTV values greater than 120 form one group. Missing CLTV values form one group. Negative CLTV values form one group. Note that, following Bartlett et al. (2022), applications that have LTV values lower than 30 or greater than 130 are dropped so that the sample conforms to the purchasing requirements of the government-sponsored entities (GSEs). CLTV accounts for other debt associated with the property over and above the loan being considered.

DTI Indicator Variables – Applications are sorted into groups according to the loan's DTI value. DTI values between 0 and 30 form 5-point groups. DTI values between 31 and 60 form 1-point groups. DTI values from 61 to 80 form one group. DTI values from 81 to 100 form one group. DTI values greater than 100 form one group. Missing DTI values from one group. Negative DTI values form one group.

Applicant Credit Score Indicator Variables – Applications are sorted into groups according to the applicant's credit score. Credit scores from 620 to 849 are broken into 10-point groups. Credit scores of 850 or greater form a group. To conform to the GSEs' purchasing requirements, applications where the main applicant's credit score is lower than 620 are dropped.

Co-applicant Credit Score Indicator Variables – Applications are sorted into groups according to the co-applicant's credit score. Missing credit scores form one group. Negative credit scores form one group. Credit scores between 0 and 299 form one group. Credit scores from 300 to 499 are broken down into two 100-point groups. Credit scores from 500 to 579 form one group. Credit score values from 580 to 849 are broken into 10-point groups. Credit scores of 850 or greater form a group.

Co-applicant Indicator Variables – An indicator variable that equals one if the application has two applicants and zero otherwise.

Age Group Indicator Variables – A set of indicator variables that captures the age group in which the applicant associated with each loan application belongs to. The age groups are 18 to 24, 25 to 29, 30 to 39, 40 to 49, 50 to 59, 60 to 69, 70 or older, and missing age. The regression uses mortgages associated with applicants in the first age group as the reference group. The missing age group indicator variable is included in the estimation but omitted from the regression outputs.

Female – An indicator variable that equals one if there is at least one female applicant associated with the loan application and zero otherwise.

Asian – An indicator variable that equals one if there is at least one Asian applicant associated with the loan application and zero otherwise.
Black – An indicator variable that equals one if there is at least one Black applicant associated with the loan application and zero otherwise.
Hispanic – An indicator variable that equals one if there is at least one Hispanic applicant associated with the loan application and zero otherwise.
Other Minority – An indicator variable that equals one if there is at least one minority applicant who is not Asian or Black associated with the loan application and zero otherwise.
Unknown Sex – An indicator variable that equals one if there is at least one applicant whose sex is unknown and zero otherwise.
Both Sexes – An indicator variable that equals one if, for at least one applicant, the applicant reported being both male and female and zero otherwise.
Unknown Race – An indicator variable that equals one if there is at least one applicant whose race is unknown and zero otherwise.
Unknown Ethnicity – An indicator variable that equals one if there is at least one applicant whose ethnicity is unknown and zero otherwise.
Automated Underwriting System (AUS) Approved – An indicator variable that equals one if the loan application was approved by at least one AUS and zero otherwise.

Tract Quarter-Control Variables (CHMDA)
Median Credit Score – The median main applicant credit score among mortgage applications that were submitted in the tract-quarter observation. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.
Median LTV – The median LTV among mortgage applications that were submitted in the tract-quarter observation. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.
Median DTI – The median DTI among mortgage applications that were submitted in the tract-quarter observation. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.
Median Income – The median applicant income among mortgage applications that were submitted in the tract-quarter observation. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.
Median Age – The median applicant age among mortgage applications that were submitted in the tract-quarter observation. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.
Asian Share – The share of applications that have at least one Asian borrower. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.
Black Share – The share of applications that have at least one Black borrower. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.
Hispanic Share – The share of applications that have at least one Hispanic borrower. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.

Female Share – The share of applications that have at least one female borrower. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.
Share of Applications with Two Borrowers – The share of applications that have two borrowers. The variable is calculated separately for treated and control mortgage applications and included in the regressions accordingly.

Lender-Quarter Control Variables (CHMDA)
Lender-quarter control variables are constructed with the same logic as the tract-quarter control variables.

Call Report Variable Definition
Mortgage Loan Growth – The growth rate of mortgage loans held on the lender's balance sheet in a given year-quarter. The growth rate is constructed as the difference between the natural log of the quantity of interest in period $t+1$ and the natural log of the quantity of interest in period t.
Commercial and Industrial (C&I) Loan Growth [0:$1m] – The growth rate of small C&I loans ($1 million or lower) held on the lender's balance sheet in a given year-quarter. The growth rate is constructed as the difference between the natural log of the quantity of interest in period $t+1$ and the natural log of the quantity of interest in period t.
C&I Loan Growth [0:$100k] – The growth rate of small C&I loans ($100,00 or lower) held on the lender's balance sheet in a given year-quarter. The growth rate is constructed as the difference between the natural log of the quantity of interest in period $t+1$ and the natural log of the quantity of interest in period t.
C&I Loan Growth [$100k:$250k] – The growth rate of small C&I loans (between $100,000 and $250,000) held on the lender's balance sheet in a given year-quarter. The growth rate is constructed as the difference between the natural log of the quantity of interest in period $t+1$ and the natural log of the quantity of interest in period t.
C&I Loan Growth [$250k:$1m] – The growth rate of small C&I loans (between $250,000 and $1 million) held on the lender's balance sheet in a given year-quarter. The growth rate is constructed as the difference between the natural log of the quantity of interest in period $t+1$ and the natural log of the quantity of interest in period t.
Ln(Assets) – The natural logarithm of total assets (RCON 2170) in each quarter.
Assets Growth – The growth rate of total assets (RCON 2170) in each quarter.
ROE – The return on equity, defined as the net income before discontinued operations (RIAD 4300) divided by total bank equity capital (RCON 3210) in each quarter.
Capital Ratio – The capital ratio, defined as the total bank equity capital (RCON 3210) divided by total assets (RCON 2170) in each quarter.
Deposit/Assets – The ratio of non-interest-bearing deposits (RCON 6631) plus interest-bearing deposits (RCON 6636) to total assets (RCON 2170) in each quarter.

CoreLogic Variable Definition
% Speculative Transactions – The percentage of transactions associated with second/investment homes in a given tract and year-quarter.
% Primary Transactions – The percentage of transactions associated with primary residences in a given tract and year-quarter.

% Corporate Transactions – The percentage of transactions associated with corporate buyers in a given tract and year-quarter.
 # Speculative Transactions – The number of transactions associated with second/investment homes in a given tract and year-quarter.
 # Primary Transactions – The number of transactions associated with primary residences in a given tract and year-quarter.
 # Corporate Transactions – The number of transactions associated with corporate buyers in a given tract and year-quarter.

Small Business Lending Variable Definition
Ln(1 + CRA Lending) – The natural logarithm of one plus the lender's Community Reinvestment Act (CRA) small business lending in a given county-year.
Ln(1 + 2020 Speculative Sold to GSEs) – The natural logarithm of one plus the speculative mortgage loan portfolios sold to GSEs by lenders in each county during the year 2020. This variable is not time varying, meaning that a specific combination of lender and county will have an unchanging value across all years.

Real Effects Variable Definition
Ln(1 + One Unit Permits) – The natural logarithm of one plus the number of building permits for one-unit structures in a specified county-quarter combination.
Ln(1 + Construction Employment) – The natural logarithm of one plus the employment level of the residential construction workers in a specified county-quarter combination.
Ln(Avg Construction Worker's Wage) – The natural logarithm of the average wage of the residential construction workers in a specified county-quarter combination.
County Level Treatment Intensity – The treatment intensity variable calculated at the county level.
Unemployment Rate – The county-level unemployment rate in a given year.
GDP Growth – The county-level GDP growth rate in a given year.
Ln(Per Capita Income) – The natural logarithm of the county-level per capita income in a given year.

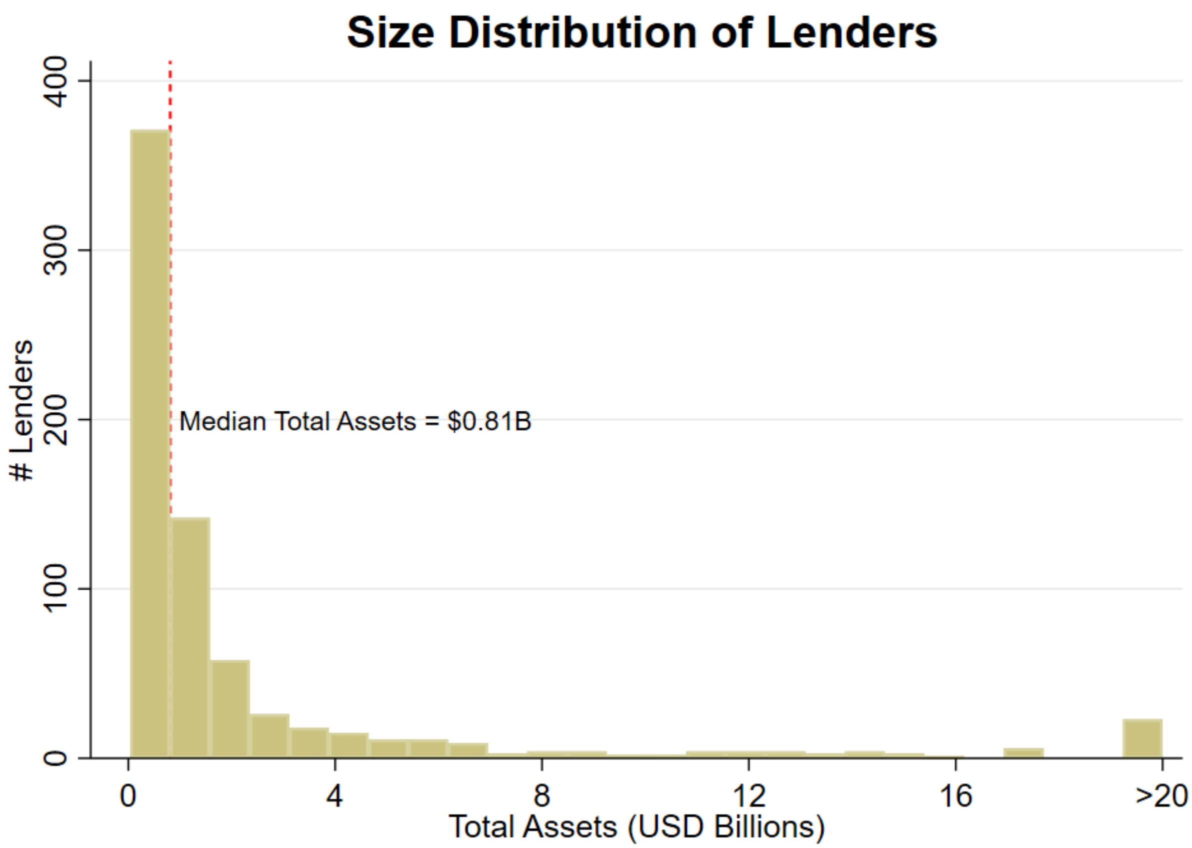


Figure IA.1 Size of Distribution of Lenders

This figure plots the size, measured by total assets, of the distribution of lenders in our sample. The vertical dotted line marks the median size of the lenders in our sample. Data source: Call Report.

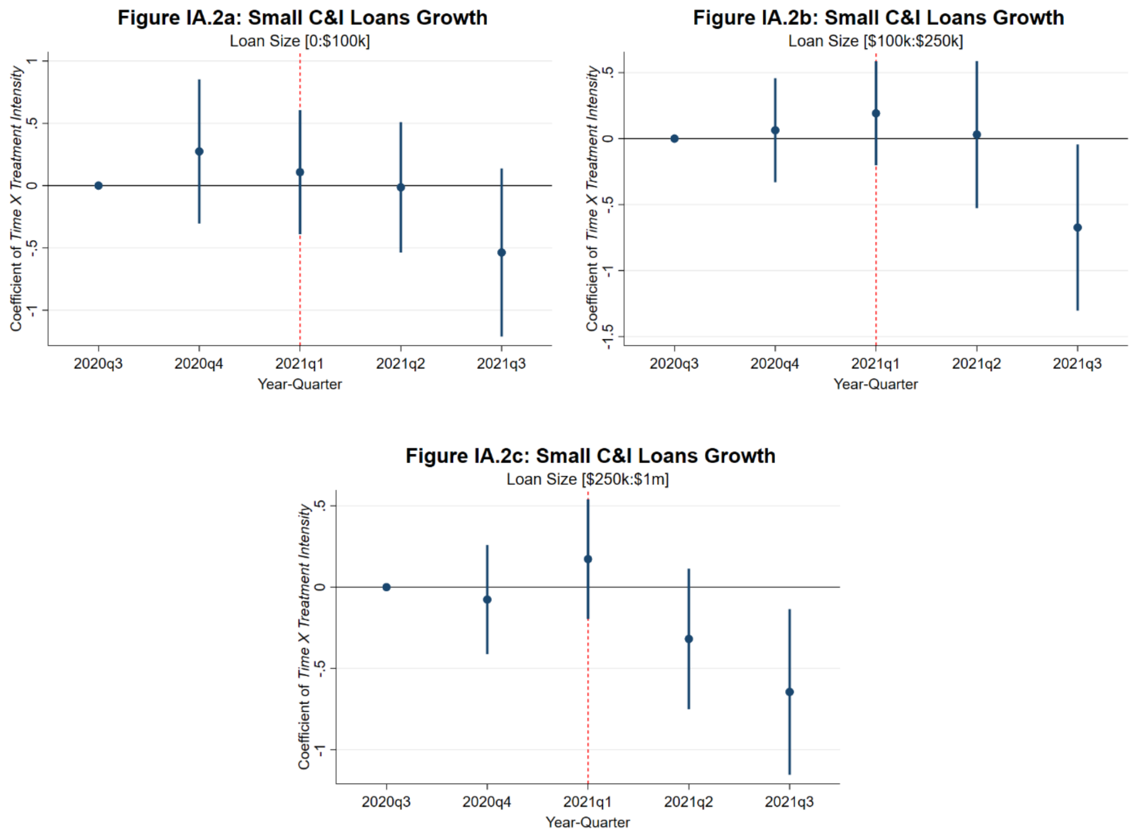


Figure IA.2 Parallel Trends for C&I Loan Growth

This figure plots coefficients and 95 percent confidence intervals from a bank-quarter-level OLS regression where the growth rate of small C&I loans held on the lender's balance sheet is regressed onto year-quarter indicator variables that interacted with the lender-level GSE purchase cap policy treatment intensity variable. The growth rate is constructed as the difference between the natural log of the quantity of interest in period *t+1* and the natural log of the quantity of interest in period *t*. Treatment intensity is a measure of each lender's exposure to the policy in the pre-period, explained in the main text. The outcome variable for Figure IA.2a is the growth rate of small C&I loans ($100,000 or lower) held on the lender's balance sheet in a given year-quarter. The outcome variable for Figure IA.2b is the growth rate of small C&I loans (between $100,000 and $250,000) held on the lender's balance sheet in a given year-quarter. The outcome variable for Figure IA.2c is the growth rate of small C&I loans (between $250,000 and $1 million) held on the lender's balance sheet in a given year-quarter. The regression specification includes control variables outlined in the Internet Appendix, lender fixed effects, and year-quarter fixed effects. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. The sample is composed of lenders with above median total assets in our sample (>$809 million USD). Heteroskedasticity-robust standard errors are clustered at the lender level. Data source: Call Report.

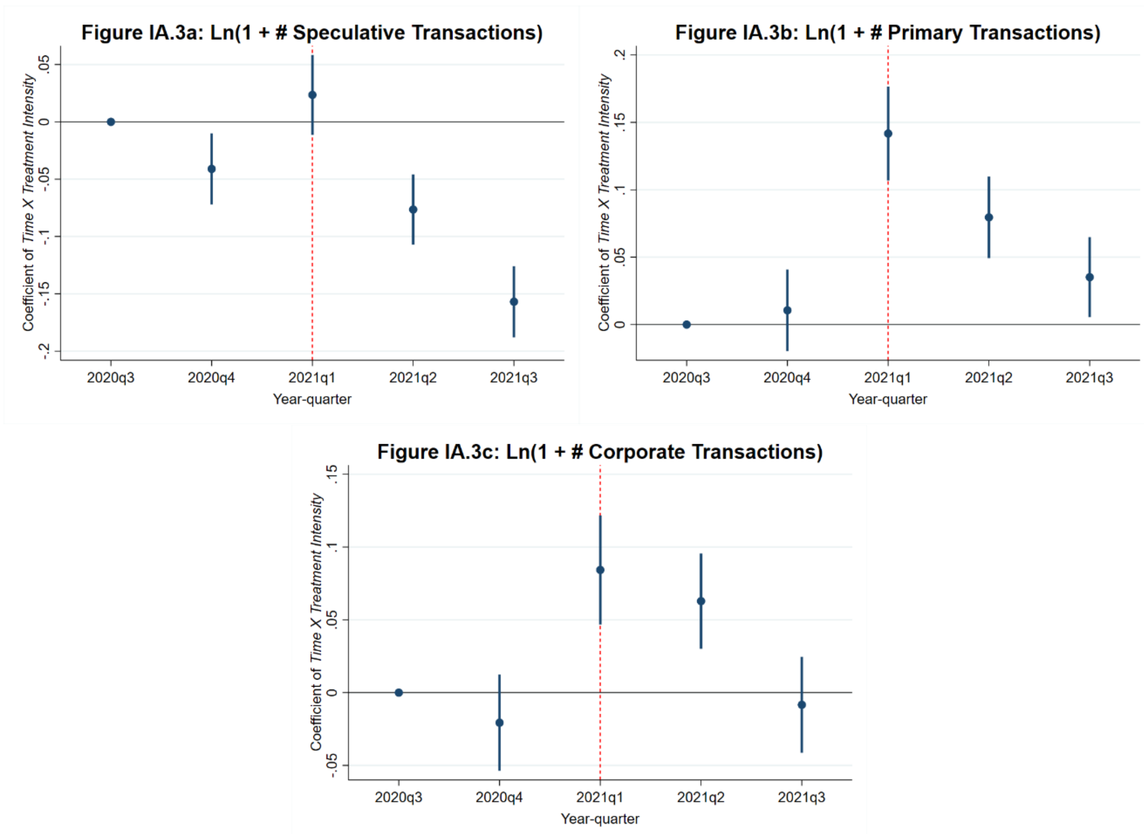


Figure IA.3 Parallel Trends for House Transactions

This figure plots coefficients and 95 percent confidence intervals from a tract-quarter-level OLS regression where the log of one plus the number of speculative, primary, and corporate transactions of single-family houses are separately regressed onto year-quarter indicator variables that interacted with the tract-level GSE purchase cap policy treatment intensity variable. The outcome variable for Figure IA.3a is the natural logarithm of one plus the number of transactions associated with second/investment homes in a given tract and year-quarter. The outcome variable for Figure IA.3b is the natural logarithm of one plus the number of transactions associated with primary residences in a given tract and year-quarter. The outcome variable for Figure IA.3c is the natural logarithm of one plus the number of transactions associated with corporate buyers in a given tract and year-quarter. Treatment intensity is a measure of each tract's exposure to the policy in the pre period, explained in the main text. The regression specification includes control variables outlined in the Internet Appendix, tract fixed effects, and year-quarter fixed effects. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. The sample is composed of transactions of single-family houses. Heteroskedasticity-robust standard errors are clustered at the lender level. Data source: CoreLogic.

Table IA.1 Summary Statistics of Control Variables (CHMDA)

This table presents summary statistics for CHMDA mortgage variables that were used in our empirical analyses. The sample period is from Q3:2020 to Q3:2021. Refer to the Internet Appendix for additional details on variable definitions. Data source: CHMDA.

	Mean	Median	S.D.	N
	(1)	(2)	(3)	(5)
Panel A: Loan level				
Application characteristics				
Age	41.97	39	14	3,748,163
Female	0.59	1	0	3,748,311
Unknown gender	0.06	0	0	3,748,311
Black	0.06	0	0	3,748,311
Hispanic	0.12	0	0	3,748,311
Asian	0.10	0	0	3,748,311
Other minority	0.01	0	0	3,748,311
Unknown race	0.15	0	0	3,748,311
Unknown ethnicity	0.15	0	0	3,748,311
Co-applicant indicator	0.40	0	0	3,748,311
Loan amount (USD Thousands)	301.89	275.00	153.58	3,748,311
Applicant credit score	754.51	763	43	3,748,311
Co-applicant credit score	760.66	772	47	585,499
Income (USD Thousands)	114.71	94	78	3,710,608
CLTV (%)	83.24	85.00	13.56	3,727,349
DTI (%)	35.48	36.50	9.99	3,733,359
AUS approved	0.94	1	0	3,748,311
Panel B: Tract-quarter level				
Speculative				
Median credit score	765.50	773	33.73	205,236
Median CLTV	0.76	1	0.09	201,469
Median DTI	0.35	0	0	199,053
Median income (USD thousands)	169.89	141	119	202,506
Median loan amount (USD thousands)	229.42	193.86	148.51	205,236
Median age	48.40	48.00	10.73	205,213
Asian share	0.14	0.00	0.29	205,236
Black share	0.05	0.00	0.19	205,236
Hispanic share	0.11	0.00	0.26	205,236
Female share	0.54	0.50	0.40	205,236
Two borrowers share	0.42	0.40	0.40	205,236
Risky				
Median credit score	758.20	763	26.07	337,683
Median CLTV	0.84	1	0.08	335,078
Median DTI	0.35	0	0	337,148
Median income (USD thousands)	98.27	88	47	337,358
Median loan amount (USD thousands)	262.24	226.75	151.63	337,683
Median age	40.69	39.00	8.41	337,677

Asian share	0.09	0.00	0.18	337,683
Black share	0.07	0.00	0.16	337,683
Hispanic share	0.13	0.04	0.22	337,683
Female share	0.58	0.60	0.24	337,683
Two borrowers share	0.39	0.38	0.24	337,683
Safe				
Median credit score	755.93	760	27.55	330,512
Median CLTV	0.85	1	0.09	327,331
Median DTI	0.35	0	0	330,276
Median income (USD thousands)	91.16	82	43	330,292
Median loan amount (USD thousands)	267.76	232.80	150.86	330,512
Median age	39.73	38.00	8.79	330,507
Asian share	0.08	0.00	0.17	330,512
Black share	0.07	0.00	0.03	330,512
Hispanic share	0.14	0.00	0.23	330,512
Female share	0.58	0.60	0.25	330,512
Two borrowers share	0.38	0.38	0.25	330,512
Panel C: Lender-quarter level				
Lender characteristics				
ROE	0.07	0.06	0.05	2,697
Capital ratio	0.11	0.10	0.02	2,697
Deposit ratio	0.83	0.84	0.06	2,697
Total assets (USD millions)	12704.32	1289.70	48166.82	2,697

Table IA.2 GSE Purchase Cap Policy and Refinance Mortgage GSE Sale Probability

This table presents mortgage-level OLS regression results where the GSE sale indicator is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable equals one if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. Speculative equals one for mortgage applications associated with second/investment homes and zero for safe mortgage applications associated with primary residences. Risky equals one for risky mortgage applications associated with primary residences and zero for safe mortgage applications associated with primary residences. Refer to the main text for details on the definition of "risky." Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. The sample includes conforming home purchase mortgages that were originated between Q3:2020 and Q3:2021. Refer to the main text for details on sample construction. Refer to this Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

Panel A: Speculative versus Safe

	P(GSE Sale)*100		
	(1)	(2)	(3)
Speculative	-3.93**	-3.92**	-0.09
	[1.75]	[1.58]	[0.57]
Speculative x Announcement	-4.17***	-4.13***	-3.64***
	[1.62]	[1.59]	[1.33]
Speculative x Implementation	-22.28***	-21.27***	-25.07***
	[3.01]	[2.93]	[3.36]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,315,573	3,314,298	3,313,670
R-squared	0.06	0.11	0.64

Panel B: Risky versus Safe

	P(GSE Sale)*100		
	(1)	(2)	(3)
Risky	0.54	0.12	0.40
	[1.17]	[2.72]	[0.99]
Risky x Announcement	-0.88	-0.77	0.14
	[1.24]	[1.13]	[0.48]
Risky x Implementation	0.32	0.95	1.08*
	[1.20]	[1.20]	[0.65]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,004,586	3,002,715	3,002,164
R-squared	0.07	0.14	0.61

Table IA.3 GSE Purchase Cap Policy and Refinance Mortgage Application Rejections

This table presents application-level OLS regression results where the application rejection indicator is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable equals 100 if the mortgage application was rejected and zero otherwise. Speculative equals one for mortgage applications associated with second/investment homes and zero for safe mortgage applications associated with primary residence. Risky equals one for risky mortgage applications associated with primary residence and zero for safe mortgage applications associated with primary residence. Refer to the main text for details on the definition of "risky." Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. The sample includes conforming home purchase mortgage applications where the approval/rejection decision was made between 2020Q3 and 2021Q3. Refer to the main text for details on sample construction. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

Panel A: Speculative versus Safe

	P(Rejected)*100		
	(1)	(2)	(3)
Speculative	3.09***	2.07***	2.88***
	[0.62]	[0.58]	[0.57]
Speculative x Announcement	-1.18***	-0.60***	-0.75***
	[0.29]	[0.23]	[0.24]
Speculative x Implementation	0.73	-0.75	-0.97
	[0.68]	[0.73]	[0.76]
Year-Quarter FE	Y	Y	Y
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,760,199	3,758,619	3,757,968
R-squared	0.04	0.32	0.39

Panel B: Risky versus Safe

	P(Rejected)*100		
	(1)	(2)	(3)
Risky	46.94***	10.93***	7.53***
	[1.70]	[1.99]	[1.01]
Risky x Announcement	1.03	-0.37	0.20
	[1.21]	[0.58]	[0.63]
Risky x Implementation	-6.65***	-5.40***	-4.08***
	[1.31]	[0.99]	[1.28]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,507,604	3,505,313	3,504,671
R-squared	0.09	0.37	0.43

Table IA.4 GSE Purchase Cap Policy and Refinance Mortgage Interest Rates

This table presents mortgage-level OLS regression results where the interest rate is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable is the interest rate of the mortgage at origination, expressed in basis points. Speculative equals one for mortgage applications associated with second/investment homes and zero for safe mortgage applications associated with primary residences. Risky equals one for risky mortgage applications associated with primary residences and zero for safe mortgage applications associated with primary residences. Refer to the main text for details on the definition of "risky." Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. The sample includes conforming home purchase mortgages that were originated between Q3:2020 and Q3:2021. Refer to the main text for details on sample construction. Refer to this Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

Panel A: Speculative versus Safe

	Interest Rate (bps)		
	(1)	(2)	(3)
Speculative	34.14***	33.71***	34.39***
	[0.93]	[1.07]	[1.21]
Speculative x Announcement	-4.14***	-3.60***	-3.48***
	[0.60]	[0.64]	[0.83]
Speculative x Implementation	3.04***	4.17***	3.64***
	[1.08]	[0.93]	[0.87]
Year-Quarter FE	Y	Y	Y
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,314,679	3,313,404	3,312,775
R-squared	0.25	0.36	0.49

Panel B: Risky versus Safe

	Interest Rate (bps)		
	(1)	(2)	(3)
Risky	12.31***	0.18	2.08*
	[0.78]	[1.83]	[1.17]
Risky x Announcement	-2.31**	-3.22***	-3.53***
	[0.96]	[0.70]	[0.71]
Risky x Implementation	6.58***	0.47	-0.41
	[1.09]	[0.83]	[0.65]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Control		Y	Y
Lender x Year-Quarter FE			Y
SE Cluster	Lender	Lender	Lender
Observations	3,071,057	3,069,456	3,068,813
R-squared	0.19	0.33	0.47

Table IA.5 GSE Purchase Cap Policy and Lender Home Purchase Mortgage Supply

This table presents OLS regression results where log origination volume, in nominal U.S. dollars, is regressed onto GSE purchase cap policy treatment intensity variables. Each observation is a bank by year-quarter. The outcome variable for column 1 is the natural log of one plus the total amount, in nominal U.S. dollars, of conforming home purchase mortgages associated with second/investment homes that were originated in a given bank and year-quarter. The outcome variable for column 2 is the natural log of one plus the total amount, in nominal U.S. dollars, of risky conforming home purchase mortgages associated with primary residences that were originated in a given bank and year-quarter. The outcome variable for column 3 is the natural log of one plus the total amount, in nominal U.S. dollars, of safe conforming home purchase mortgages associated with primary residences that were originated in a given bank and year-quarter. Announcement equals one for Q1:2021 and zero otherwise. Implementation equals one for Q2:2021 and Q3:2021 and zero otherwise. Treatment intensity is a measure of each bank's exposure to the policy in the pre-period, explained in the main text. The application pool characteristic control variables are constructed for the respective loan category (speculative, risky, or safe). Refer to the main text for details on sample construction. Refer to this Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the bank level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

	Ln(1 + Origination Volume)		
	Speculative	Risky	Safe
	(1)	(2)	(3)
Treatment Intensity x Announcement	0.181	-0.002	0.455
	[0.496]	[0.459]	[0.324]
Treatment Intensity x Implementation	-1.547***	-0.132	0.161
	[0.435]	[0.347]	[0.237]
ROE	0.157	-0.509	-0.601**
	[0.411]	[0.366]	[0.260]
Capital Ratio	-4.297**	3.252*	1.296
	[2.150]	[1.775]	[1.819]
Deposit Ratio	-0.102	-0.751**	-0.210
	[0.599]	[0.371]	[0.403]
Ln(Total Assets)	0.216	0.499**	0.510***
	[0.179]	[0.204]	[0.174]
Median Credit Score 1 = 100	0.372***	-0.011	0.107
	[0.098]	[0.030]	[0.086]
Median CLTV 1 = 100%	0.229	0.285	0.011
	[0.518]	[0.367]	[0.280]
Median DTI 1 = 100%	0.000	-0.105	0.032
	[0.293]	[0.151]	[0.362]
Median Income 1 = 100K	-0.052	0.024	0.088
	[0.038]	[0.053]	[0.107]
Median Loan Amount 1 = 100K	0.308***	0.035*	0.226***
	[0.038]	[0.018]	[0.048]
Asian Share 1 = 100%	0.447***	0.115	0.357
	[0.140]	[0.089]	[0.285]
Black Share 1 = 100%	0.640**	-0.090	-0.448
	[0.303]	[0.098]	[0.389]
Hispanic Share 1 = 100%	-0.020	0.078*	-0.224
	[0.139]	[0.042]	[0.177]
Female Share 1 = 100%	0.044	0.011	-0.184

	[0.243]	[0.068]	[0.293]
Two-Borrowers Share 1 = 100%	0.064	-0.080	0.201
	[0.141]	[0.051]	[0.165]
Median Age	-0.003	0.001	-0.007**
	[0.003]	[0.001]	[0.003]
Lender FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
SE Cluster	Lender	Lender	Lender
Observations	2,695	2,129	2,404
R-squared	0.603	0.968	0.977

Table IA.6 Spillover Effects on CRA Lending – Expanded Sample

This table presents OLS regression results at the county-lender-year level, where the outcome variable, the log of one plus the lender's CRA lending, is regressed onto the log of one plus the lender's speculative loans sold to the GSEs in 2020. We use the 2021 indicator variable to identify the policy's treatment period. The sample includes (1) lender-county pairs that have non-zero CRA lending during 2019–2021 and those that originated and sold some speculative loans to GSEs in 2020, the treatment exposure; (2) lender-county pairs that made no CRA lending during 2019–2021 and have positive treatment exposure; and (3) lender-county pairs that have non-zero CRA lending during 2019–2021 but have no treatment exposure. Columns 1 and 2 report the results for the 2019–2021 sample, while columns 3 and 4 report the results for the 2020–2021 sample. Heteroskedasticity-robust standard errors are double clustered at both the lender level and the county level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data sources: CRA, CHMDA.

	(1) Ln(CRA Lending + 1)	(2) Ln(CRA Lending + 1)	(3) Ln(CRA Lending + 1)	(4) Ln(CRA Lending + 1)
Ln(2020 Speculative Mortgages Sold to GSEs + 1)	0.152***		0.138***	
	[0.010]		[0.011]	
2021 * Ln(2020 Speculative Mortgages Sold to GSEs + 1)	-0.016***	-0.016***	-0.002	-0.002
	[0.004]	[0.004]	[0.005]	[0.005]
Lender-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Lender-County FE		Y		Y
Sample	2019-2021	2019-2021	2020-2021	2020-2021
Cluster	County and Lender	County and Lender	County and Lender	County and Lender
Observations	724,227	724,227	482,818	482,818
R-squared	0.498	0.824	0.504	0.870

Table IA.7 Spillover Effects on Jumbo Mortgage Lending – Expanded Sample

This table presents OLS regression results at the county-lender-year level, where the outcome variable, the log of one plus the lender's jumbo mortgage lending, is regressed onto the log of one plus the lender's speculative loans sold to the GSEs in 2020. We use the 2021 indicator variable to identify the policy's treatment period. The sample includes (1) lender-county pairs that have non-zero jumbo mortgage lending during 2019–2021 and those that originated and sold some speculative loans to GSEs in 2020, the treatment exposure; (2) lender-county pairs that made no jumbo mortgage lending during 2019–2021 and have positive treatment exposure; and (3) lender-county pairs that have non-zero jumbo mortgage lending during 2019–2021 but have no treatment exposure. Columns 1 and 2 report the results for the 2019–2021 sample, while columns 3 and 4 report the results for the 2020–2021 sample. Heteroskedasticity-robust standard errors are double clustered at both the lender level and the county level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

	(1) Ln(Jumbo Originations + 1)	(2) Ln(Jumbo Originations + 1)	(3) Ln(Jumbo Originations + 1)	(4) Ln(Jumbo Originations + 1)
Ln(2020 Speculative Mortgages Sold to GSEs + 1)	0.099***		0.097***	
	[0.012]		[0.012]	
2021 * Ln(2020 Speculative Mortgages Sold to GSEs + 1)	-0.144***	-0.144***	-0.142***	-0.142***
	[0.010]	[0.010]	[0.010]	[0.010]
Lender-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Lender-County FE		Y		Y
Sample	2019-2021	2019-2021	2020-2021	2020-2021
Cluster	County and Lender	County and Lender	County and Lender	County and Lender
Observations	391,419	391,419	260,946	260,946
R-squared	0.353	0.652	0.360	0.730

Table IA.8 Spillover Effects on Jumbo Mortgage Lending – Quarterly Test

This table presents OLS regression results at the county-lender-quarter level, where the outcome variable, the log of one plus the lender's jumbo mortgage lending, is regressed onto the interaction between the log of one plus the lender's speculative loans sold to the GSEs in 2020, the treatment exposure, and the announcement indicator variable or the implementation indicator variable, both defined in the same way as in previous tables. The sample period spans Q3:2020 to Q3:2021. The sample includes lender-county pairs that have non-zero jumbo mortgage lending during Q3:2020 to Q3:2021 and those that have non-zero treatment exposure. Heteroskedasticity-robust standard errors are double clustered at both the lender level and the county level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

	(1) Ln(Jumbo Originations + 1)	(2) Ln(Jumbo Originations + 1)
Ln(2020 Speculative Mortgages Sold to GSEs + 1)	1.823***	
	[0.066]	
Announcement * Ln(2020 Speculative Mortgages Sold to GSEs + 1)	-0.046	-0.046
	[0.062]	[0.062]
Implementation * Ln(2020 Speculative Mortgages Sold to GSEs + 1)	-0.028	-0.028
	[0.057]	[0.057]
Lender-Quarter FE	Y	Y
County-Quarter FE	Y	Y
Lender-County FE		Y
Cluster	County and Lender	County and Lender
Observations	110,730	110,730
R-squared	0.393	0.562

Table IA.9 Spillover Effects on Jumbo Mortgage Lending – Quarterly Test with Expanded Sample

This table presents OLS regression results at the county-lender-quarter level, where the outcome variable, the log of one plus the lender's jumbo mortgage lending, is regressed onto the interaction between the log of one plus the lender's speculative loans sold to the GSEs in 2020, the treatment exposure, and the announcement indicator variable or the implementation indicator variable, both defined in the same way as in previous tables. The sample period spans Q3:2020 to Q3:2021. The sample includes (1) lender-county pairs that have non-zero jumbo mortgage lending during Q3:2020 to Q3:2021 and those that have non-zero treatment exposure; (2) lender-county pairs that made no jumbo mortgage lending during Q3:2020 to Q3:2021 and have positive treatment exposure; and (3) lender-county pairs that have non-zero jumbo mortgage lending during Q3:2020 to Q3:2021 but have no treatment exposure. Heteroskedasticity-robust standard errors are double clustered at both the lender level and the county level. *, **, and *** denote 10 percent, 5 percent, and 1 percent statistical significance levels, respectively. Data source: CHMDA.

	(1) Ln(Jumbo Originations + 1)	(2) Ln(Jumbo Originations + 1)
Ln(2020 Speculative Mortgages Sold to GSEs + 1)	0.102***	
	[0.013]	
Announcement * Ln(2020 Speculative Mortgages Sold to GSEs + 1)	-0.006	-0.006
	[0.008]	[0.008]
Implementation * Ln(2020 Speculative Mortgages Sold to GSEs + 1)	-0.037***	-0.037***
	[0.009]	[0.009]
Lender-Quarter FE	Y	Y
County-Quarter FE	Y	Y
Lender-County FE		Y
Cluster	County and Lender	County and Lender
Observations	547,515	547,515
R-squared	0.298	0.587