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ABSTRACT

In 2021, the U.S. Treasury reduced Government Sponsored Enterprises (GSEs) exposure to speculative mortgages. As a result, GSE purchases fell by about 20 percentage points. The policy reduced credit to speculative investors in housing, but increased credit to unaffected parts of the conforming-mortgage market. Banks responded by reallocating provision of speculative mortgage credit across their local markets, which in turn affected their provision of small business credit. These adjustments are most pronounced where banks do not own branches. The results suggest that banks manage credit provision not only in a macro sense – the focus of most research – but also market-by-market.

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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 prior to 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 declines 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 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. The amendment imposed caps on the GSEs' ability to invest in both high-risk loans (limiting exposure to low FICO-score borrowers, to high loan-to-value loans, and to high debt-to-income borrowers) and loans for housing speculation (defined as mortgages for either second homes or investment properties). We study the impact of these changes on credit

[1] We define speculative transactions in the real estate market as household purchase of non-owner-occupied homes (Chinco and Mayer, 2016; Defusco, Nathanson and Zwick, 2022). This method has been widely used in the literature and is considered as the real time proxy for speculative housing investment (Guren, 2022).

[2] Both the Obama and Trump Administrations made efforts to re-privatize Fannie Mae and Freddie Mac. As of this writing, the two GSEs remain under government ownership and control.

supply, housing 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.[3] We also find important second-order effects, as the changes in GSE policies spill-over into unaffected segments, including low-risk mortgages, high-risk but non-speculative mortgages, and small business loans.

We first focus on the conforming mortgage markets, where the GSEs are active, to 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.[4] This non-result squares with existing evidence (which we verify) that the limits on high-risk mortgages in the PSPA were rarely binding prior to the pandemic (Golding et al., 2021); hence, this part of the policy mattered little. There is no 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.

Despite this large overall drop, we show that banks skew their sales of speculative mortgages toward riskier ones after the policy caps go into effect. This adjustment partially offsets the larger aim of the policy change, which is to lower risk-exposure of the GSEs. Based on our regression analysis, mortgages to borrowers with a FICO score that is one standard deviation below

[3] In this paper we use the word banks and lenders interchangeably to mean all lenders that participated in the U.S. mortgage and show up in the CHMDA data. The only exceptions are the local spillover effects analyses (Tables 7 and 8) where we only include banks in the sample because we study the interaction between the purchase cap policy and the presence of bank branches.
[4] Throughout the paper, we use the term “high-risk” and “risky” interchangeably to refer to the set of non-speculative conforming mortgages that the PSPA limited the GSEs’ ability to invest in.

average are about one percentage point more likely to be sold after the policy, and mortgages with CLTV that is one standard above average are more than three percentage points more likely to be sold.

Next, we explore how lenders adjust credit supply when the GSEs reduce their purchase activities in the secondary 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. 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 loans sold to the GSEs – experience relative declines in both speculative mortgage originations and mortgage applications. A one-standard-deviation increase in treatment intensity for a given tract leads to about 8% less 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/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 to speculative mortgages by increasing supply in both the low-risk as well as high-risk but non-speculative segments of the conforming mortgage market. We show that both rejection rates and interest rates decline for high-risk mortgages.[5] In addition, overall originations (and applications) of both safe and risky (non-speculative) mortgages increase in areas most affected by the policy caps. Hence, supply *declines* in the speculative segment but *increases* in the other parts of the conforming loan market.

Third, we test for local effects, both direct (effects on the speculative segment) and indirect (effects on the jumbo-mortgage segment as well as the market for small business loans). For these tests we construct a three-way panel dataset at the bank-county-year level, which allows us to test how banks' allocation of mortgages *across* their markets changes in response to the policy.[6] By absorbing bank-year fixed effects, we remove all lender heterogeneity and thus focus solely on how different levels of pre-policy, bank-market-level exposure changes origination behavior. Moreover, we use this framework to test whether a bank's local presence, based on whether or not it has at least one branch in a given county, affects its response. We show that banks that had sold more speculative loans from a given county before the policy reallocated their originations away from those areas (relative to other areas served by that bank). However, this reallocation is substantially smaller in areas with branches. This finding supports Cortes (2015), who finds that banks with a local branch presence have superior information about housing prices. Our results suggest that banks continue to supply credit to speculative borrowers in localities where they have an informational advantage, despite being forced by the policy to hold these loans rather than sell them to third parties.[7]

[5] These results represent comparisons to the safe, conforming mortgage segment, which we use as the reference group in our difference-in-differences approach.

[6] We expand the time dimension from quarterly to annually because the data are too sparse at the bank-quarter-county level for the jumbo market, and, for the small business lending data, we only have annual data . In these tests, we compare 2020 as the base year and 2021 as the treatment year.

[7] In these tests, we also consider the possibility that banks continue to make speculative mortgages in areas with branches in order to meet compliance tests associated with the Community Reinvestment Act. In fact, we find that branch presence dominates the CRA requirement, consistent with an information channel.

We then document local credit spillovers to the market for small business lending, although not to the jumbo market. In other words, banks' origination of small business loans – a market *not* directly affected by the policy – also declines in local areas where the bank had greater exposure to the purchase caps (but did not own branches). The spillover suggests information synergy, as banks which reduce lending in speculative mortgage markets may lose information about the local market. Hence, a decline in speculative lending leads them to lend less to local businesses, even though these borrowers are not affected by the policy. We find no adjustment in the growth of small business loans, however, in markets where banks own branches. That is, banks reduce credit in markets where they have withdrawn due to the policy shock (markets where they *do not* own branches), and they continue to lend in markets where the policy shock had little impact (markets where they *do* own branches). Since the policy has no direct impact on small business lending, we infer a synergy across lending types.[8]

Finally, we explore the policy's effects on local housing activity and local real outcomes. We first focus on both changes in housing transactions and house prices. The policy spurs an increasing share of homes purchased by corporate investors, such as private equity firms, who partially replace capital formerly supplied by small investors buying second homes (who 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. Despite these adjustments, we find that house-price growth slows in markets more exposed to the policy caps. We also test for, but do not find, declines in the

[8] Jumbo lending may not respond because these are heavily securitized in the so-called private-label market. In fact, these securitizations hit a post-GFC high in 2021, nearing 50%. See https://www.corelogic.com/intelligence/2021-a-banner-year-for-jumbo-loan-securitization/.

construction sector in more affected areas. Because the policy was only in effect for less than one full year, its impact on real outcomes may have been attenuated.

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 MBS 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 which 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), focusing on differences between non-jumbo and jumbo segments of the market. Using a similar approach, several papers focus 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 sub-prime and Alt-A mortgage markets during the 2000-2006 boom by buying high-risk mortgages and also purchasing private-label mortgage-backed securities (Calomiris and Walison, 2009). Scharfstein and Sunderam (2013) show that the level of pass-through of GSE funding 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 (Agarwal, Badarinza and Qian, 2018; Agarwal et al., 2021; Deng et al., 2019; Deng et al., 2022; Fu, Qian and Yeung, 2016; and Chi, LaPoint and Lin, 2020). A number of papers that study the U.S. housing markets have emphasized the important role speculators play in both volume and house-price dynamics (DeFusco, Nathanson and Zwick, 2022; Nathanson and Zwick, 2018), as well as their role in mispricing (Chinco and Mayer, 2016) and potentially destabilizing housing markets (Gao, Sockin and Xiong, 2020; Mian and Sufi, 2022; Garcia, 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 the two GSEs and grants the government control of ownership (79.9% 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 dividends 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 their 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% of home purchase mortgages and 3% of refinancing mortgages, based on a trailing 52-week period. High risk mortgages are those with two or more of: combined loan-to-value (CLTV) greater than 90%; debt-to-income ratio greater than 45%; and credit score less than 680. In addition, the amendment limits the GSE acquisition of mortgages secured by second homes or investment properties (which we will refer to as "speculative mortgages") to 7% of single-family acquisitions over the preceding 52-week period. The Purchase Cap policy was announced on January 14, 2021 and went into effect on April 1, 2021, but was suspended in September 2021. In January of 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 imposing hard constraints; this change effectively pushed in the same direction as the original policy, but with somewhat weaker effects.[9]

Given this history, we focus on the five quarters which 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. For most of our analysis 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 markets and the broader economy. We drop the quarters after 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% 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% for purchase mortgages and 3% for refinance). As we will show, the policy likely had large effects on credit in the speculative market, but limited ones for non-speculative 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.

[9] See https://home.treasury.gov/news/press-releases/sm1236.

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 mortgages held by originating banks increases sharply (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.

Our empirical design exploits the time series variation in the GSE Purchase Caps interacted 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, for both, 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 prior to the policy's announcement.

3. Empirical Methods and Results

We report tests at the loan-level, the market level (census tract and county) and the lender-market 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 tract level and test how the policy affects origination and application volumes.

These two tests establish how the policy affects credit supply in the conforming mortgage markets. Third, we expand the panel to the bank-county-time level to test for local effects; this empirical strategy allows us to fully remove both bank-time and county-time effects, thus zeroing in on reallocation of credit across a given bank's markets. 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 the Home Mortgages Disclosure Act (HMDA) data, and 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 which are not financed with mortgages (and hence do not appear in HMDA), such as all-cash deals as well as those made by corporate investors such as private equity firms.[10] 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 the Quarterly Census of Employment and Wages data from the Bureau of Labor Statistics to obtain the county-level employment information of construction workers.

Table 1 reports summary statistics, for our samples at the different levels of aggregation. Panel A reports loan-level statistics; Panel B reports statistics at the tract-year-quarter level; Panel

[10] The GSEs require borrowers to be natural persons. Exceptions include (1) inter vivos revocable trusts, (2) HomeStyle Renovation mortgages, and (3) land trusts in those states where the beneficiary is an individual. See https://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 Seller Guide.

C reports statistics at the lender-county-year-quarter level; Panel D reports statistics of house transactions from CoreLogic at the tract-year-quarter level.

3.1 GSE Purchase Cap Policy and Conforming-Mortgage Lending

Following several papers in the mortgage lending literature (Bhutta et al., 2020; Bhutta et al., 2021; Bartlett et al., 2022; Amornsiripanitch, 2023), we construct our sample from first-lien home purchase, single-family, 30-year fixed-rate conventional conforming mortgage applications and originations.[11] To ensure that we only include conforming mortgages, we follow the GSE seller's guide and loan-level price adjustment (LLPA) documents and we drop mortgage applications where the main borrower's credit score is lower than 620, the loan amount exceeds the conforming loan limit, and at least one automated underwriting system (AUS) flagged the mortgage application as being ineligible for GSE purchase.[12] We also exclude government guaranteed mortgages such as VA, 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 2020Q3 and 2021Q3, inclusive. Finally, we drop mortgage applications associated with manufactured homes. The filters leave us with approximately 3.75 million home purchase mortgage applications.[13]

We divide our sample into three segments. Speculative mortgages are those backed by second homes or investment properties. Risky mortgages are those that are backed by primary

[11] 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.
[12] See https://selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/ for Fannie Mae's Selling Guide and https://singlefamily.fanniemae.com/media/9391/display its LLPA matrix.
[13] In the period of analysis, there were 4.17 million first-lien home purchase, single-family, 30-year fixed-rate conventional conforming mortgage. Therefore, we end up dropping approximately 10% of this sample.

residences (i.e., non-speculative) but meet at least two of the following "risky" criteria: (i) cumulative loan-to-value (CLTV) ratio above 90%; (ii) debt-to-income (DTI) ratio above 45%; and, (iii) 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 variants of the following loan-level regression:

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

where *i* refers to loan, *j* refers to lender, *k* refers to census tract, and *t* refers to year-quarter.[14]

The dependent variable in Equation (1) is an indicator set to one hundred for rejected applications, an indicator for originated mortgages sold to Fannie Mae or Freddie Mac by the end of reporting calendar year, or the loan interest rate expressed in basis points. The coefficients labeled δ_k and $\gamma_{j,t}$ indicate tract and lender by year-quarter fixed effects. We estimate the equation using the linear probability model, given the large number of fixed effects. $Treated_i$ equals one if mortgage application i is associated with second or investment homes and zero otherwise, following Gao, Sockin, and Xiong (2020); alternatively, $Treated_i$ equals one if mortgage application i is backed by a primary residence property but meets at least two risk metrics defined above. In some columns, we also report models without lender-year-quarter fixed effects. Control (i.e., safe) mortgage applications are those associated with conforming mortgages

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

that do not qualify as either Speculative or Risky. $Announcement_t$ equals one for 2021Q1 and zero otherwise; $Implementation_t$ equals one for 2021Q2 and 2021Q3 and zero otherwise.

We also include the following loan-level controls: borrower characteristics (borrower's age (Amornsiripanitch, 2023), gender, race, ethnicity, credit score, income, and debt-to-income (DTI)) and loan characteristics (loan amount, cumulative loan-to-value (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 the lender level, again as indicated in the tables.

Recall that Figure 2 suggests that the Purchase Caps bind for speculative mortgages but not risky mortgages. Table 2 supports this claim, after partialling out fixed effects and control variables. Panel A presents the regression results for GSE sale probability, comparing speculative to safe primary mortgages. In all three columns, the coefficient estimates for *Speculative x Announcement* and *Speculative x Implementation* are negative and statistically significant. After the policy was announced, second/investment home mortgages are 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., 2021Q2 to 2021Q3). 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 takes effect. This represents a reduction of 35% when compared to the average sales probability of 62%.

Panel B of Table 2 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.

Table 3 tests whether the change in selling behavior varies with mortgage risk. We introduce interaction effects between the policy-cap indicators and three standard risk metrics: 1) the borrower's credit score (FICO); 2) CLTV; and 3) DTI ratio. Two of these interact significantly with the post-implementation indicator. For the credit score, a one-standard-deviation decrease in FICO (=~ 40 points) lowers the effect of the policy cap on sales by about 0.8 percentage points (= -40 x -0.02). The effect of CLTV is larger: a one-standard-deviation increase (=14.3) reduces the policy cap's effect on sales by about 3.6 percentage points (=14.3 x 0.249).[15] In other words, the distribution of loans sold after the policy skews toward those with greater risk. Thus, banks offset some of the policy's intended effects, which were to reduce GSE risk exposure. The same results hold when we include LLPA grid by year-quarter fixed effects to control for lenders' incentive to sell loans with respect to the GSEs' guarantee fees (Bartlett et al., 2022). In untabulated results, we have also considered whether ex-post risk (i.e., defaults) of sold loans increases after the policy but find limited statistical power in these tests.

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 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

[15] See Appendix Table IA.1 for summary statistics on loan characteristics.

for risky mortgages. The 13 basis point increase is modest, representing a 4.2% increase compared to 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:

$$y_{i,t} = \alpha + \delta_k + \gamma_{j,t} + \sum_t \beta_t Month_t \times Speculative_i + \beta_{July,2020} Speculative_i + Control\,Variables + \epsilon_{i,t}, \qquad \textit{Eq. 2}$$

where *Month*$_t$ equals one for year-month t and zero otherwise; δ_k and $\gamma_{j,t}$ indicate tract and lender by year-month fixed effects. The β_t coefficients are month-specific difference-in-differences (DiD) coefficients (with July 2020 acting as the reference month). 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 begin at announcement (not before), and then grow in magnitude after implementation; since we find no effects before announcement, 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 loan interest rates; here, rates rise only after the policy goes into effect (as opposed to starting to adjust at announcement). For all three outcomes there is no evidence of pre-announcement period effects.

Tables 4-5 provide some evidence that the policy reduces credit supply for speculative mortgages (due to higher interest rates) and, if anything, *increases* supply for non-speculative but risky mortgages (due to the lower rejection rates). This makes sense because the policy itself had a very large effect on lender sales of speculative loans to the GSE, but no effect on their sales of risky but non-speculative loans (Table 2). Hence, banks responded by increasing their willingness to originate those risky loans that they could continue to sell during the policy period.[16] 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

We construct a tract-year-quarter panel dataset, starting with all conforming conventional home purchase mortgage applications that were accepted or denied between 2020Q3 and 2021Q3. We sum across loan amounts to compute the total quantity of credit for each tract-year-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 were 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 and Farmer Mac 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.

We report regressions analogous to Equation (1) above, although now the models are true panels. The dependent variable equals either the log of the total originations or total applications for tract j in year-quarter t. Each model is reported separately for quantities based on whether or not 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

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

percentage of second/investment home mortgages purchased by the GSEs for mortgages originated in tract j in 2020 (i.e., before the policy announcement). As in the loan-level regressions, $Announcement_t$ equals one for 2021Q1 and zero otherwise; $Implementation_t$ equals one for 2021Q2 and 2021Q3 and zero otherwise. Because the loan-level analysis establishes no effect on sales in the risky segment, we do not construct a treatment intensity metric for these loans; instead, we use the *Treatment Intensity* for speculative ones. Hence, we interpret the coefficient in the risky segment as a spillover effect of the policy's impact on speculative lending.

For the origination volume regressions, control variables at the tract-year-quarter level include median CLTV, median DTI, median income, median age, Asian share, Black share, Hispanic share, Female share, and share of applications with two borrowers. The control variables can be thought of as the observable application and applicant characteristics that determine the lender's origination decision. For the application volume regressions, we do not include any control variables because, by the same logic, we do not observe determinants of borrowers' application decisions. Additional details on the control variables are described in the Internet Appendix. We also include tract and year-quarter fixed effects. Heteroskedasticity-robust standard errors are clustered at the tract level.

Table 6 presents the results. For the tract-level speculative mortgages, the coefficient estimates for *Treatment Intensity x Announcement* and *Treatment Intensity x Implementation* are negative and statistically significant (column 1). Consistent with the loan-level results, which suggest a negative supply effect, speculative mortgage quantities fall more for tracts with higher exposure to the GSE Purchase Cap policy. This effect begins at announcement, as both coefficients are close to each other. Economically, a one-standard-deviation increase in treatment intensity for a given tract leads to an 8% (=0.16 x 0.503) drop in the second/investment home purchase mortgage supply over the policy period (2021Q2-2021Q3) compared to the pre-policy period (2020Q3-2020Q4).

The results are the opposite for both risky and safe primary home purchase mortgages (columns 2-3). Here, the policy encourages more lending in the most-affected areas. The coefficient estimates for both *Treatment Intensity x Implementation* and *Treatment Intensity x Implementation* are both positive and statistically significant, 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 4.45% (=0.297 x 0.15) increase in the risky primary home purchase mortgage supply over the policy period and a 2.3% (=0.155 x 0.15) increase in the safe primary home purchase mortgage supply over the policy period.

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. Panel B of Table 6, which focuses on applications rather than originations, reports very similar effects as in Panel A, both statistically and economically. Together with Table 2, 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 (Table 5), rather than because rejection rates increase. This can reflect banks' discouraging applicants from applying or even from banks exiting markets with high levels of speculative transactions.

Figure IA.1 plots the respective coefficients in a dynamic DiD framework. Figure IA.1a 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, its magnitude is small. In contrast, the magnitude of the coefficient estimates increase significantly after the policy was announced. Figure IA.1b plots coefficient estimates for the tract-level second/investment home purchase mortgage origination. Figures IA.1c to IA.1f plot the coefficient estimates for the parallel trends for risky and safe loans. These show that the significant effects only existed after the policy became effective.

To summarize: Purchase Caps bind strongly on speculative mortgage activity, 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 *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 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. In this section, we strip out any effect on credit at the bank-level and test, first, whether banks reallocate speculative mortgage originations across markets (i.e., away from more exposed and toward less exposed ones); and, second, whether there are local spillovers to other kinds of credit. Information synergies could motivate banks to cut back across multiple kinds of local loans in response to a decline in another. So, for example, if the bank withdraws from the speculative mortgage market due to the policy caps, it may also reduce other kinds of credit. To test this idea, we focus on small business loans and jumbo mortgages (because we can measure originations market-by-market).

To isolate the local channel, rather than estimate the overall effects at the loan or market level, we now test for effects *within* a given bank during a given period and compare how variation in exposure to the policy cap across individual markets affects lending in those localities. Thus, our measure of treatment intensity now varies at the bank-market level. This approach allows us to absorb potentially confounding effects at both the market-level and the bank-level (since we can construct a three-dimensional panel). To do so, we focus on originations of speculative mortgages as well as originations of small business loans and jumbo mortgages.

With these data, we estimate panel models, as follows:

$$LGR_{j,c,t} = \alpha + \gamma_{j,t} + \mu_{c,t} + \eta_{c,j} + \beta_1\left(Post \times \; Treatment\; Intensity_{j,c,2020}\right) \qquad \textit{Eq. 3}$$
$$+ \; Control\; Variables + \epsilon_{j,c,t} \; .$$

The panel varies across banks (*j*), counties (*c*), and years (*t*).[17] Loan growth ($LGR_{i,c,t}$) equals the growth rate of credit supply (either speculative mortgages, small business loans, or jumbo mortgages) for bank *i* in county *c*, in year *t*; *Post* is a time indicator set to one during 2021, which covers the policy-cap regime. We estimate Equation 3 with and without a branch interaction effect to test whether the policy effects differ by a bank's physical presence in the market.[18] In addition, we test whether the policy effect on loan growth depends on whether or not a county is deemed to be a CRA assessment area for a given bank for purposes of compliance with the Community Reinvestment Act (CRA).[19] Banks receive ratings from the Federal regulators based on the

[17] Unlike the earlier results, this analysis focuses on banks because the small business data are only available for them, and because we want to condition on physical proximity based on each bank's branch footprint.
[18] We utilize the FDIC Summary of Deposits data to determine if a bank has a branch presence in a specific county.
[19] Under the Community Reinvestment Act of 1977, each bank's CRA assessment areas are geographical regions utilized by regulatory agencies to assess banks' effectiveness in meeting the credit needs of its community, including, but not limited to, low- and moderate-income neighborhoods. Typically, banks have their main offices, branches, and deposit-taking ATMs within these areas (Bhutta and Canner 2009; Agarwal, Benmelech, Bergman, and Seru 2012; Avery and Brevoort 2015). Note that, at the county-level, a bank's branch footprint and its CRA assessment areas are

amount of credit originated in the CRA assessment areas, so they may be hesitant to cut originations of speculative mortgages (and other loans as well) after the policy caps go into effect, compared to other areas.[20]

We make several modeling adjustments to mitigate the problem of small lending amounts in certain cells. First, in contrast to our earlier tests, we aggregate to annual rather than quarterly (or monthly) frequency. Second, we build a modified growth rate in which the change in lending (numerator) is normalized by the mid-point between the two periods (denominator); this approach bounds the measure between +2 and -2, thus reducing volatility if either the beginning or end of period value is small (or zero). Third, we weight each bank-county-year observation by the average *level* of originations across the 2019-2021 periods. This procedure has two advantages: 1) it puts greater weight on more important markets; and 2) it mitigates the impact of high volatility in growth rates for very small markets.[21]

Since these models are estimated with bank-year fixed effects (due to inclusion of $\partial_{j,t}$), we are comparing how varying exposure to the policy cap across different markets correlates with a bank's lending decisions. Identification comes from reallocation across markets. Hence, we do not need to worry about heterogeneity at the bank level. We also remove variation in local credit demand by absorbing county-time fixed effects ($\gamma_{c,t}$), as well a variation in a bank's overall importance to a county ($\eta_{c,j}$).[22] As with the earlier measures of treatment exposure, we build *Treatment Intensity*$_{j,c,2020}$ to capture bank's market-by-market exposure to the policy caps on

not identical. In our sample, the correlation between the county-level bank branch indicator variable and the county-level CRA assessment area indicator variable is approximately 80%.

[20] Banks with low CRA ratings may face regulatory limits on their ability to expand by adding branches and/or acquiring whole banks.

[21] In the results reported below, the weights are winsorized at the 1% level to mitigate the impact of extreme values.

[22] The results are similar without bank-county fixed effects.

speculative mortgages based on the ratio of its 2020 speculative loans sold to the GSEs in market *c*, divided by its total speculative loan originations across all markets.[23] 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. Our coefficient of interest, β_1, tests whether banks move funds away from more-affected markets due to the policy (the direct effect of $\textit{Treatment Intensity}_{j,c,2020}$ is absorbed).

To test whether the policy effects spillover to other types of local loans, we focus on jumbo mortgages (which are not purchased by the GSEs, either before or after the policy) and small business loans. We obtain small business loan data from the Community Reinvestment Act (CRA) database. This information details small business lending (commercial and industrial loans with commitment 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 dataset to calculate the lenders' county-level origination of speculative and jumbo mortgages at the lender-county-year level. The CRA data also have information on which counties are CRA assessment areas for each bank, which we use to build the *CRA Assessment Area* flag.

The results in Tables 7 and 8 provide strong evidence that banks reduce their exposure to both speculative mortgages (the direct effect of the policy) and small business lending (the indirect effect), mostly in markets where they have high exposure to the purchase caps. But this effect is dominated by areas where banks *do not* own branches. Banks thus reallocate their lending across markets in response to the policy. The fixed effects rule out explanations related to the lender's overall risk exposure, or its focus on any given market, or demand for either loan type at the market

[23] We find similar results if we normalize the treatment intensity measure by its total speculative loan sold to the GSEs across all markets. However, this approach (unlike the one we use) does not capture differences across banks in their overall propensity to rely on the GSEs for speculative lending.

level. From column 1 Table 7A, the effect of *Treatment Intensity* is negative and significant, but this effect is significantly smaller (i.e., the *Branch* interaction is positive) in counties where banks own branches (columns 2 and 4). The coefficients suggest that a one-standard-deviation increase in *Treatment Intensity* reduces speculative loan growth by 13% (=0.03 x -4.369) in markets without branches, but by only 6% (=0.03 x (-4.369+2.370)) in markets with branches. In contrast, we find no significant differential impact of the policy in a bank's CRA assessment areas once we control for branch location (column 4).

In contrast, we find no response in the origination of jumbo mortgages (Table 7B). Jumbo lending may not respond because, unlike small business loans, they are heavily securitized in the so-called private-label market. In fact, these securitizations hit a post-GFC high in 2021, nearing 50%.

Table 8 reports similar specifications for the growth in small business loans. Here the difference between markets with and without branches is even more stark. In markets without a branch, banks reduce small business lending growth by about 7.5% for a one-standard-deviation increase in *Treatment Intensity* (=0.02 x -3.781), which is approximately equal to the unconditional average growth in these loans. In contrast, there is no significant change in lending growth where banks own branches, i.e., the sum of the direct effect of *Post x Treatment Intensity*, plus its interaction with the branch indicator is approximately zero.

Taken together, these results suggest that banks respond to the policy caps on speculative mortgages by exiting markets in which they have no comparative advantage – that is, areas without branch presence. This, in turn, leads them to cut back on small business credit in those same areas, suggesting a synergy between different kinds of local lending. In contrast, banks reduce speculative lending very little, and small business lending not at all, in markets where they have a branch presence. We interpret these patterns as evidence that loans made near banks' branches remain profitable, even when they lose the option to sell them.

3.4 GSE Purchase Cap Policy, Housing, and Real Effects

In this section we consider the broader potential effects of the purchase caps. First, we test how both housing prices and housing transactions by different types of investors respond to the policy. Based on CoreLogic data, we can separate transactions into those made by corporate investors, who may be able to substitute for the reduction of investors relying on bank credit, as well as residential investors by type (speculative v. non-speculative or primary). Second, we test whether the policy has real effects, focusing on employment in the construction sector and construction activity.

We first estimate the average tract-level, quarterly effect of the GSE purchase cap policy on housing investments by using the shares and the transaction volume of housing transactions, subdivided into speculative transactions, corporate transactions, and primary transactions, as the outcome variables.[24] These regressions have the same structure as those reported earlier in Table 6. Speculative transactions are defined as non-owner-occupied home purchases. We identify the household purchase of non-owner-occupied homes based on the buyers' mailing addresses on the deed and the physical address of the property, following (Chinco and Mayer, 2016; Defusco, Nathanson, and Zwick, 2022).[25] Corporate transactions are defined based on whether houses are purchased by corporate buyers, as indicated in the raw data by CoreLogic. Primary residence

[24] 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 tract-level speculation and price appreciation, and adding a measure of market 'hotness' (i.e., tract-level pre-policy price appreciation) to our model, along with its interaction with the policy shocks, has little impact on the results.
[25] We cannot use the approach (buy and sell within 3 years) from Defusco, Nathanson, and Zwick (2022) because of our limited sample period.

transactions are home purchases of owner-occupied properties, again, identified based on comparing the buyers' mailing addresses on the purchase deed with the physical address of the property. These data represent the entire housing market, including cash-financed deals, as captured by CoreLogic.

In Panel A of Table 9, 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 that 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 x 0.033), a 2.2% drop compared to the sample average percentage of second/investment home transactions (24%). 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.

Panel B of Table 9 reports transaction volumes using the number of transactions (rather than percentages). Transaction volumes have a strong seasonal component which varies across markets, so we remove this variation, following the procedure outlined in Berger et al. (2020).[26]

[26] 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-adjustment parameter at the

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. 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 which had been financed by individuals prior to the exit of the GSEs. As in the earlier analysis, with one exception, Figure IA.2 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 10 reports similar tract-level regression results of house price growth (mean and median). These suggest that the policy reduced housing price appreciation. The magnitude of this effect, however, is modest. For example, a one-standard-deviation increase in *Treatment Intensity* lowers the growth of prices at the median by less than 1%. This small effect is likely due to the increase in housing investment from sources which do not rely on GSE subsidies (as shown in Table 9). Consistent with the evidence on transaction volumes, Figure IA.3 shows an absence of any pre-trend.

Table 11 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. We keep the same five quarters as our

county-quarter level. We divide the actual number of housing transactions in each tract and quarter from 2020Q3 to 2021Q3 by its respective county-quarter-level seasonality adjustment parameter to get the seasonally-adjusted number of housing transactions in each tract and quarter.

baseline regression, 2020Q3 to 2021Q3. Policy effective period is a dummy variable set to one for 2021Q2 to 2021Q3. The Treatment Intensity variable is computed using the same method as our treatment intensity calculation at the tract level but applied at the county level instead. We find no evidence that real economic activity declined due to the policy, although these tests are likely under-powered 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. Banks reallocate credit for speculative mortgages away from markets where they are most exposed to the policy but have no branch presence; these adjustments, in turn, also lead to declines in small business lending. In contrast, we find small effects of the policy on mortgage lending in markets where banks have branches, and no lending spillovers in those markets. 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. Housing prices fall modestly in response to the policy, but we find no evidence of real effects.

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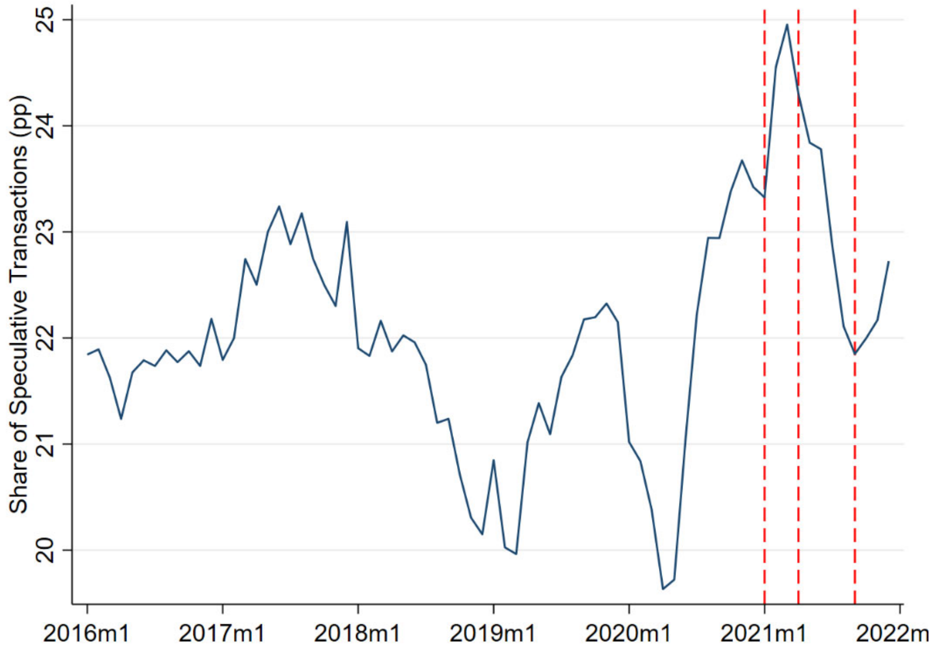


Figure 1: Nationwide Fractions of Speculative Transactions

Figure 1 illustrates the nationwide seasonality adjusted trends of speculative transactions, spanning 2016 to 2021. 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 Category

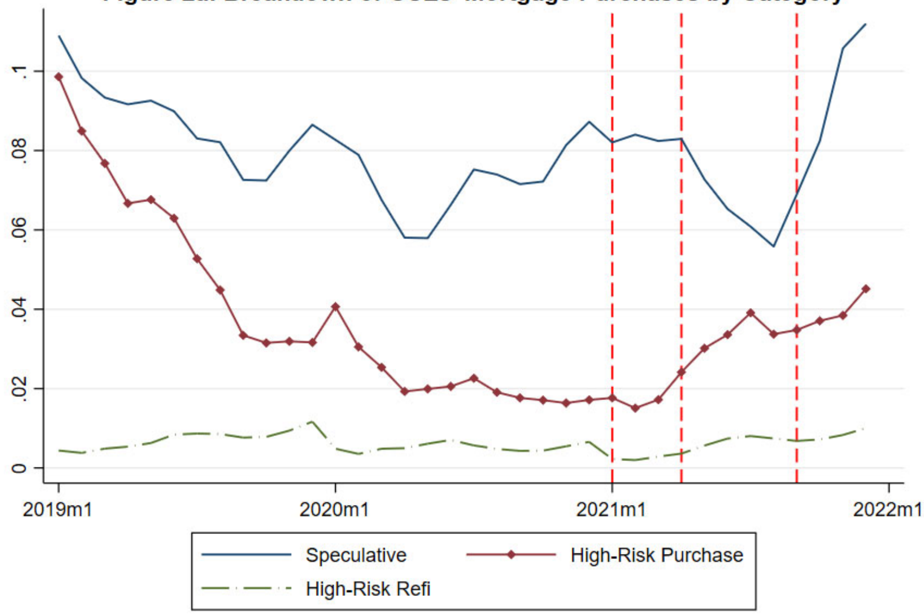
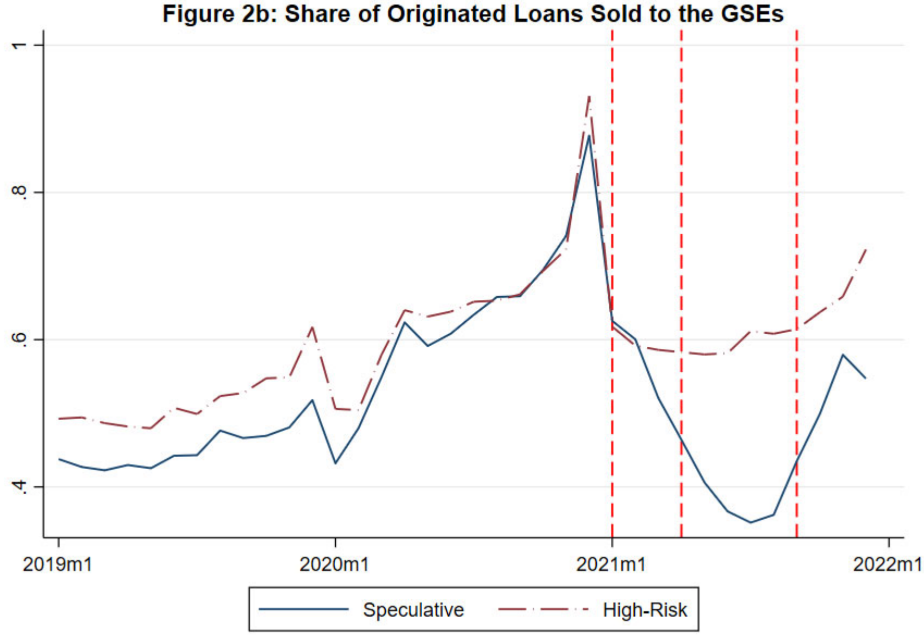


Figure 2b: Share of Originated Loans Sold to the GSEs



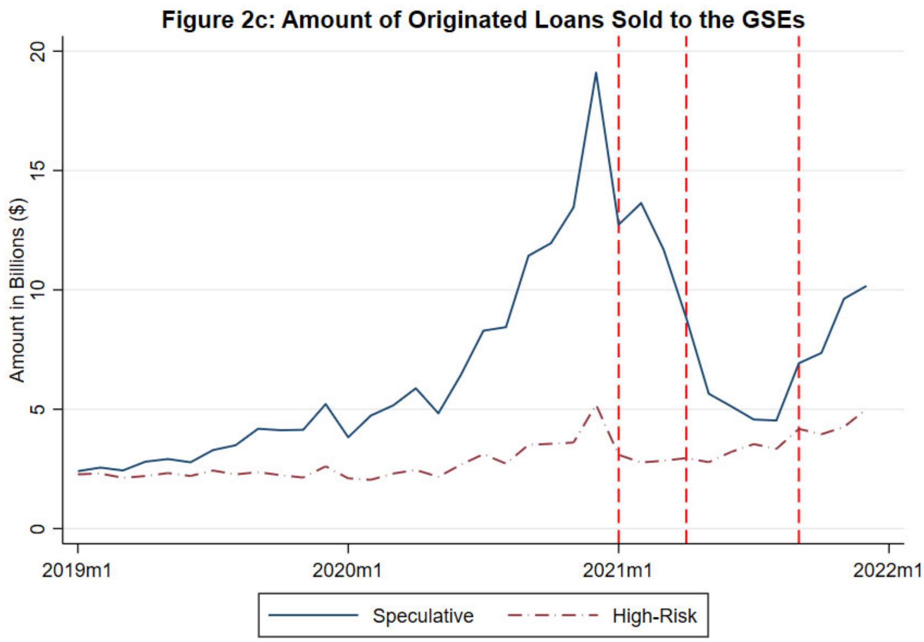


Figure 2c: Amount of Originated Loans Sold to the GSEs
Amount in Billions ($)
0
5
10
15
20
2019m1
2020m1
2021m1
2022m1
Speculative
High-Risk

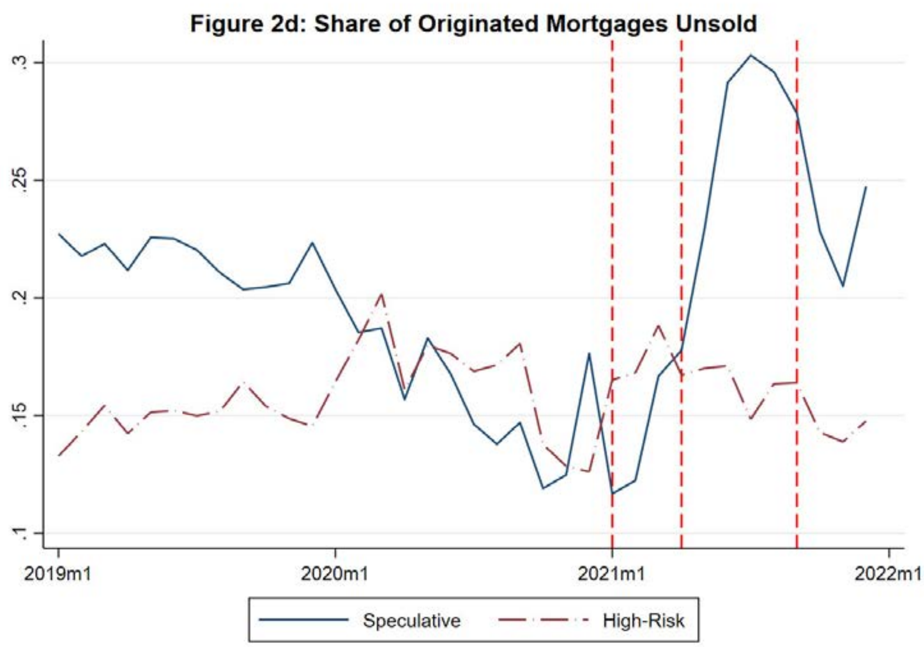


Figure 2d: Share of Originated Mortgages Unsold
.1
.15
.2
.25
.3
2019m1
2020m1
2021m1
2022m1
Speculative
High-Risk

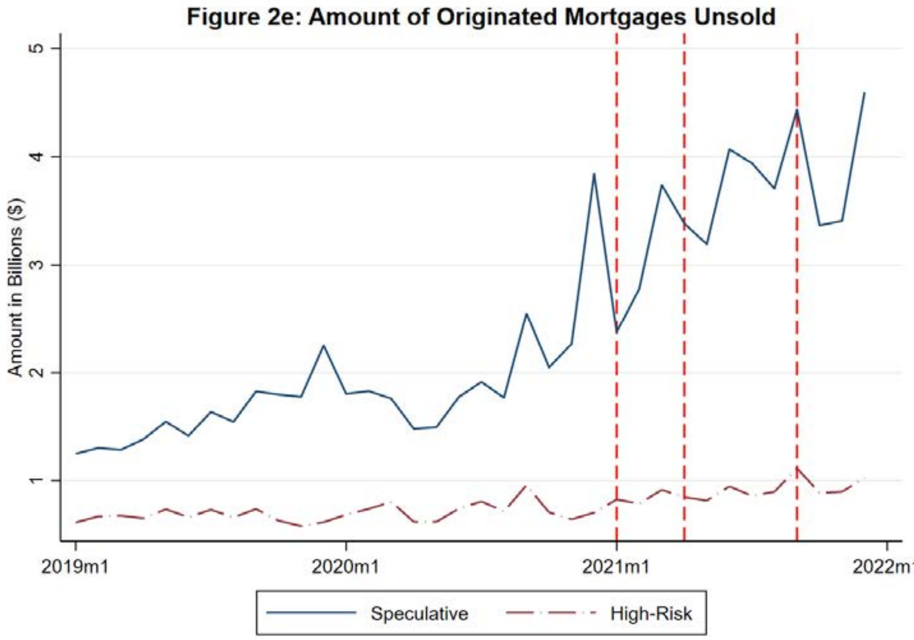
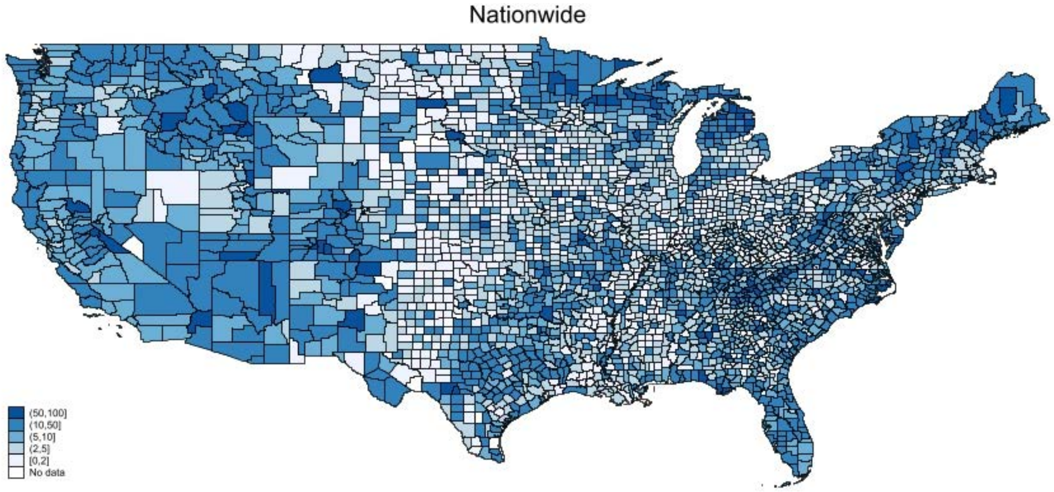


Figure 2: Time Series Plots of CHMDA Mortgage Trends

Figures 2a to 2e display nationwide trends in 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 backed by second or 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 amount of speculative mortgages held on lenders' balance sheets and the amount 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: CHMDA.

Panel A: County-Level Exposure



Panel B: Tract-Level Exposure in Major Cities

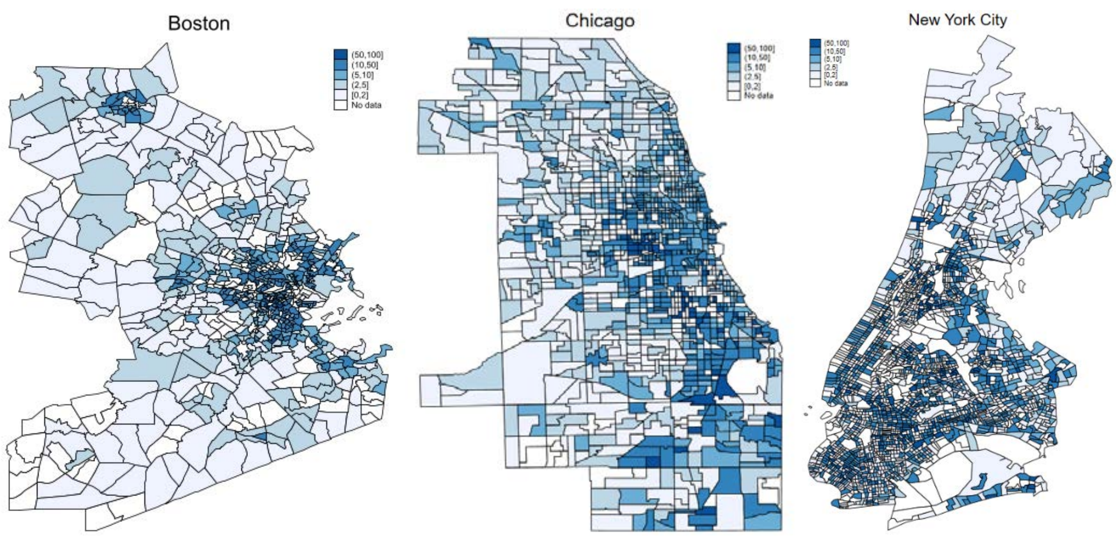


Figure 3. Geographic Exposure to the GSE Purchase Cap Policy

Panel A plots county-level exposure to the GSE Purchase Cap policy across the United States. County-level exposure to the GSE Purchase Cap 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 GSE Purchase Cap policy in three major cities: Boston, Chicago, and New York. Tract-level exposure to the GSE Purchase Cap policy is computed as the percentage of second/investment home backed mortgages that the GSEs purchased in each census tract in 2020.

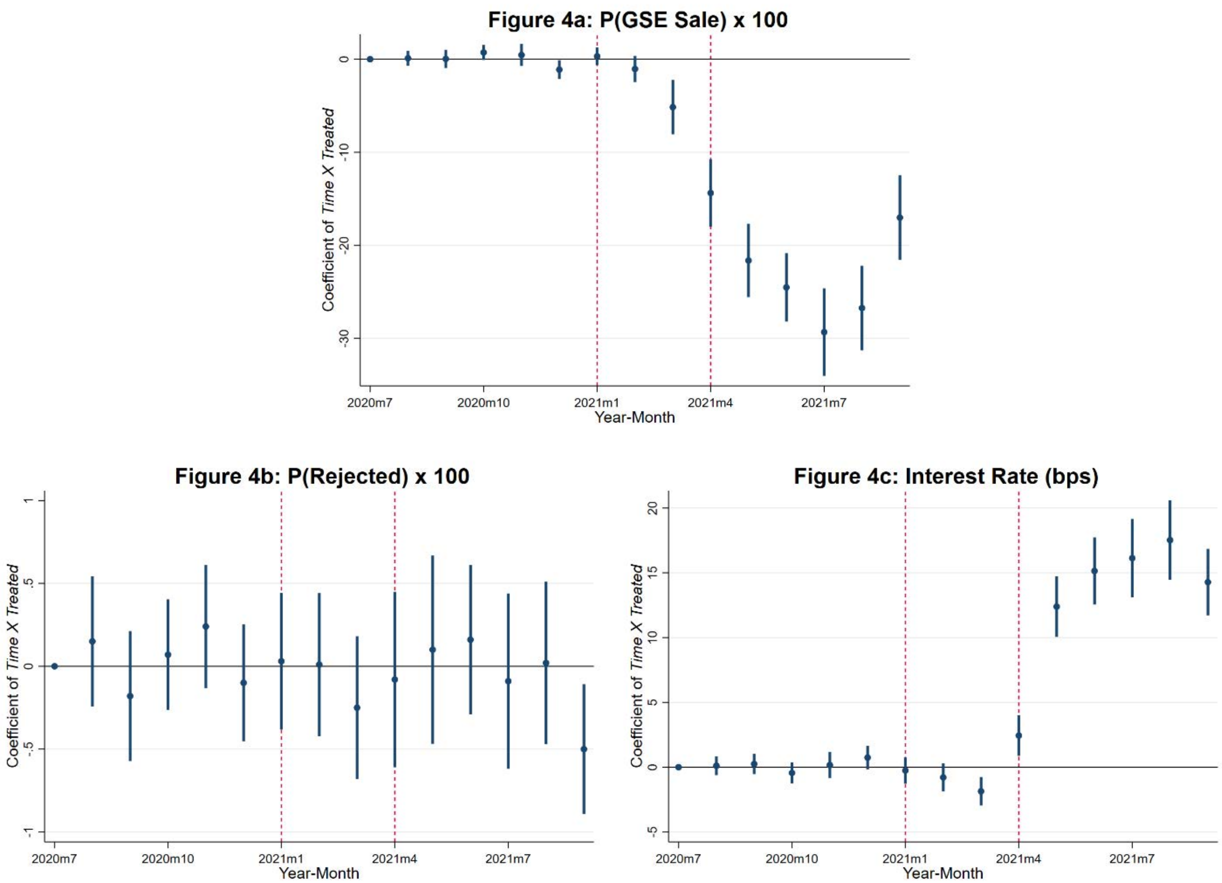


Figure 4. Loan-Level Parallel Trend Regressions

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

Table 1. Summary Statistics

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

VARIABLES	Mean	Median	S.D.	N
	(1)	(2)	(3)	(5)
Panel A: loan level				
Outcome variable				
Rejected	0.06	0	0.23	3,748,311
GSE Sale	0.62	1	0.48	3,459,418
Interest Rate (bps)	307.07	299.90	37.43	3,457,395
Policy exposure (Loan)				
Speculative Mortgage	0.13	0.00	0.34	3,748,311
Risky Mortgage	0.07	0.00	0.26	3,748,311
Borrower Credit Quality				
Applicant Credit Score	754.51	763	43	3,748,311
CLTV (%)	83.24	85.00	13.56	3,727,349
DTI (%)	35.48	36.50	9.99	3,733,359
Panel B: tract-quarter level				
Application volume (USD millions), including zeroes:				
Speculative home purchase	0.39	0.12	0.76	353,640
Risky home purchase	0.24	0.01	0.38	353,640
Safe home purchase	2.82	1.62	3.45	353,640
Origination volume (USD millions), conditional on some applications:				
Speculative home purchase	0.61	0.33	0.83	205,236
Risky home purchase	0.35	0.26	0.37	183,292
Safe home purchase	2.80	1.66	3.29	330,512
Policy exposure (Tract)				
Treatment intensity	0.11	0.05	0.16	353,640
Panel C: lender-county-quarter level				
Speculative Growth	0.15	0.16	0.76	65,777
Jumbo Growth	0.19	0.20	0.68	26,160
CRA Growth	0.09	0.05	0.85	71,797
Branch	0.36	0.00	0.48	71,797
CRA Assessment Area	0.40	0.00	0.49	71,797

Panel D: tract-quarter level house transactions (CoreLogic)				
Outcome variable				
# Speculative Transactions	3.88	2.02	5.06	329,328
# Primary Transactions	12.27	8.53	13.15	329,328
# Corporate Transactions	1.71	0.94	2.29	329,328
% Speculative Transactions	0.24	0.15	0.26	330,125
% Primary Transactions	0.62	0.70	0.29	330,125
% Corporate Transactions	0.11	0.06	0.15	330,125
Average House Price ($)	385,130	280,282	343,444	330,125
Median House Price ($)	357,732	264,000	312,603	330,125
Average House Price Growth	0.04	0.04	0.30	322,499
Median House Price Growth	0.04	0.04	0.28	322,499
Policy exposure (Tract)				
Treatment Intensity	0.11	0.05	0.16	345,490

Table 2. 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 reporting calendar year and zero otherwise. In Panel A, Speculative equals one for mortgages associated with second or investment homes and zero for safe mortgages associated with primary residence. In Panel B, Risky equals one for risky mortgages associated with primary residence and zero for safe mortgages 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 mortgages that were originated between 2020Q3 and 2021Q3. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA.

Panel A: Speculative versus Safe

	P(GSE Sale) x 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
Controls		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) x 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
Controls		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 3. GSE Purchase Cap Policy, Loan Risk, 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 reporting calendar year and zero otherwise. Speculative equals one for mortgages associated with second or investment homes and zero for safe mortgages associated with primary residence. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. Credit Score is the main applicant's credit score. CLTV is the mortgage's cumulative loan-to-value ratio. DTI is the mortgage's debt-to-income ratio. LLPA grid refers to Fannie Mae's loan-level price adjustment matrix. The sample includes conforming home purchase mortgages that were originated between 2020Q3 and 2021Q3. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA.

	P(GSE Sale) x 100	
Speculative versus Safe	(1)	(2)
Speculative	-3.601	1.750
	[2.602]	[2.477]
Speculative x Announcement	3.077	-3.898
	[3.780]	[4.055]
Speculative x Implementation	-13.040**	-21.023***
	[5.871]	[6.898]
Speculative x Credit Score	0.000	-0.002
	[0.003]	[0.003]
Speculative x Announcement x Credit Score	-0.012**	-0.004
	[0.005]	[0.005]
Speculative x Implementation x Credit Score	-0.031***	-0.020***
	[0.007]	[0.007]
Speculative x CLTV	0.058***	0.009
	[0.015]	[0.012]
Speculative x Announcement x CLTV	0.053***	0.064***
	[0.018]	[0.017]
Speculative x Implementation x CLTV	0.229***	0.249***
	[0.047]	[0.045]
Speculative x DTI	-0.010	-0.011
	[0.013]	[0.013]
Speculative x Announcement x DTI	-0.009	-0.007
	[0.019]	[0.019]
Speculative x Implementation x DTI	-0.071	-0.069
	[0.044]	[0.044]
Tract FE	Y	Y
Controls	Y	Y
Lender x Year-Quarter FE	Y	Y
LLPA Grid x Year-Quarter FE		Y
SE Cluster	Lender	Lender
Observations	3,241,425	3,241,425
R-squared	0.575	0.577

Table 4. GSE Purchase Cap Policy and Home Purchase 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. In Panel A, Speculative equals one for mortgage applications associated with second or investment homes and zero for safe mortgage applications associated with primary residence. In Panel B, 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 Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA.

Panel A: Speculative versus Safe

	P(Rejected) x 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]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Controls		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) x 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]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Controls		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 Rates

This table presents mortgage-level OLS regression results where 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 or investment homes and zero for safe mortgages associated with primary residence. In Panel B, Risky equals one for risky mortgages associated with primary residence and zero for safe mortgages 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 mortgages that were originated between 2020Q3 and 2021Q3. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: 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]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Controls		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]
Year-Quarter FE	Y	Y	
Tract FE	Y	Y	Y
Controls		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 Application and Origination Volume

This table presents OLS regression results for GSE purchase cap policy treatment intensity and lending volume. Each observation is a census tract by year-quarter. In Panel A, the dependent variables are the natural logarithms of loan origination volumes: Column 1 covers speculative mortgages, Column 2 risky mortgages, and Column 3 safe mortgages. Similarly, in Panel B, the outcome variables are the natural logarithms of loan application volumes, with Column 1 covering speculative mortgages, Column 2 risky mortgages, and Column 3 safe mortgages. Implementation equals one for 2021Q2 and 2021Q3 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 and the internet appendix. Refer to the Internet Appendix for details on the control variables. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA.

Panel A: Origination Volume

	Ln(origination volume USD)		
	Speculative	Risky	Safe
	(1)	(2)	(3)
Treatment Intensity x Announcement	-0.500***	0.198**	0.403***
	[0.023]	[0.087]	[0.021]
Treatment Intensity x Implementation	-0.503***	0.297***	0.155***
	[0.019]	[0.062]	[0.017]
Tract FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Controls	Y	Y	Y
SE Cluster	Tract	Tract	Tract
Observations	173,522	137,676	321,936
R-squared	0.804	0.549	0.879

Panel B: Application Volume

	Ln(application volume USD)		
	Speculative	Risky	Safe
	(1)	(2)	(3)
Treatment Intensity x Announcement	-0.493***	0.259***	0.421***
	[0.025]	[0.061]	[0.021]
Treatment Intensity x Implementation	-0.521***	0.222***	0.171***
	[0.020]	[0.046]	[0.018]
Tract FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Controls			
SE Cluster	Tract	Tract	Tract
Observations	194,838	172,331	329,475
R-squared	0.758	0.547	0.866

Table 7. Local Mortgage Growth

This table presents WLS regression results at the county-lender-year level, where the outcome variable, the growth rate of speculative mortgage and jumbo mortgage, are regressed onto pre-policy lender-county-level policy exposure and lenders' local branch presence. Weights are based on each bank's average origination amount of speculative mortgages (Panel A) and jumbo mortgages (Panel B) in the 2019-2021 period, winsorized at the 1% level. We use the 2021 indicator variable to identify the policy's treatment period. The outcome variable in Panel A is the growth rate of conforming home purchase and refinance mortgages associated with second or investment homes that were originated and held by a given lender in a given county-year. The outcome variable in Panel B is the growth rate of jumbo mortgages that were originated and held by a given lender in a given county-year. Treatment Intensity is calculated as the proportion of the lender's 2020 speculative loan amount sold to the GSEs in a given county relative to the total volume of speculative loans issued by the lender in 2020. Refer to the main text and the internet appendix for details on the outcome variables and the Treatment Intensity variable. Non-bank lenders are excluded from the sample. Heteroskedasticity-robust standard errors are double clustered at both the lender level and the county level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA.

Panel A: Local Speculative Mortgage Growth

	Speculative Mortgage Growth			
VARIABLES	(1)	(2)	(3)	(4)
Post x Treatment Intensity	-2.166***	-4.369***	-2.649***	-4.389***
	[0.376]	[1.144]	[0.557]	[1.151]
Post x Branch		0.108***		0.101***
		[0.028]		[0.033]
Post x Branch x Treatment Intensity		2.370**		2.271**
		[1.054]		[1.091]
Post x CRA Assessment Area			0.101***	0.010
			[0.032]	[0.037]
Post x CRA Assessment Area x Treatment Intensity			0.902	0.251
			[0.628]	[0.624]
Lender-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Lender-County FE	Y	Y	Y	Y
SE Cluster	County and Lender	County and Lender	County and Lender	County and Lender
Observations	49,384	49,384	49,384	49,384
R-squared	0.560	0.562	0.561	0.562

Panel B: Local Jumbo Mortgage Growth

	Jumbo Mortgage Growth			
VARIABLES	(1)	(2)	(3)	(4)
Post x Treatment Intensity	-0.611	-0.686	-0.696	-0.636
	[0.417]	[1.017]	[0.914]	[1.040]
Post x Branch		-0.111***		-0.036
		[0.042]		[0.050]
Post x Branch x Treatment Intensity		0.316		-0.065
		[1.027]		[1.191]
Post x CRA Assessment Area			-0.124***	-0.092
			[0.045]	[0.058]
Post x CRA Assessment Area x Treatment Intensity			0.379	0.390
			[0.955]	[1.143]
Lender-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Lender-County FE	Y	Y	Y	Y
SE Cluster	County and Lender	County and Lender	County and Lender	County and Lender
Observations	21,288	21,288	21,288	21,288
R-squared	0.605	0.607	0.607	0.607

Table 8. Spillover Effects on Local CRA Lending

This table presents WLS regression results at the county-lender-year level, where the outcome variable, the growth rate of the lenders' CRA loans, is regressed onto the pre policy lender-county level policy exposure and lenders' local branch presence. Weights are based on each bank's average origination amount of CRA loans in the 2019-2021 period, winsorized at the 1% level. We use the 2021 indicator variable to identify the policy's treatment period. Treatment Intensity is calculated as the proportion of the lender's 2020 speculative loan amount sold to the GSEs in a given county relative to the total volume of speculative loans issued by the lender in 2020. Non-bank lenders are excluded from the sample. Heteroskedasticity-robust standard errors are double clustered at both the lender level and the county level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CRA, CHMDA.

	CRA Loan Growth			
	(1)	(2)	(3)	(4)
Post x Treatment Intensity	-1.636***	-3.781**	-1.089**	-3.248**
	[0.312]	[1.597]	[0.469]	[1.515]
Post x Branch		-0.640***		-0.438***
		[0.085]		[0.081]
Post x Branch x Treatment Intensity		3.469**		3.263**
		[1.578]		[1.509]
Post x CRA Assessment Area			-0.621***	-0.258***
			[0.082]	[0.060]
Post x CRA Assessment Area x Treatment Intensity			0.951	-0.248
			[0.578]	[0.429]
Lender-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Lender-County FE	Y	Y	Y	Y
SE Cluster	County and Lender	County and Lender	County and Lender	County and Lender
Observations	64,288	64,288	64,288	64,288
R-squared	0.819	0.842	0.839	0.843

Table 9. 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, 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 the number of transactions. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 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 and the internet appendix. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CoreLogic.

Panel A: % Transactions

	% Speculative Transactions		% Primary Transactions		% Corporate Transactions	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Intensity x Announcement		-0.017***		0.009		0.005
		[0.006]		[0.007]		[0.006]
Treatment Intensity x Implementation	-0.027***	-0.033***	0.009**	0.012**	0.015***	0.017***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]	[0.005]
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)
Treatment Intensity x Announcement		0.241***		1.404***		0.437***
		[0.083]		[0.136]		[0.054]
Treatment Intensity x Implementation	-0.638***	-0.558***	0.644***	1.112***	0.104***	0.250***
	[0.060]	[0.068]	[0.085]	[0.094]	[0.038]	[0.041]
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

Table 10. GSE Purchase Cap Policy and House Prices

This table presents OLS regression results where the growth rate of average and median housing price 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 is the growth rate of average house price in a given tract and year-quarter. The outcome variable for columns 3 and 4 is the growth rate of median house price in a given tract and year-quarter. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 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 and the internet appendix. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CoreLogic.

	House Price Growth (Average)		House Price Growth (Median)	
	(1)	(2)	(3)	(4)
Treatment Intensity x Announcement		-0.066***		-0.066***
		[0.014]		[0.013]
Treatment Intensity x Implementation	-0.010	-0.032***	0.002	-0.020**
	[0.008]	[0.008]	[0.008]	[0.008]
Tract FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
SE Cluster	Tract	Tract	Tract	Tract
Observations	318,239	318,239	318,239	318,239
R-squared	0.065	0.066	0.069	0.069

Table 11. Real effects – Building Permit and Construction Employment

This table presents OLS regression results testing the real effects of the GSE purchase Cap policy. Each observation is a county and year-quarter pair. Columns 1 and 2 report the results of the growth rate of one-unit single-family house building permits. Columns 3 to 6 report the results for the growth rate of residential construction employment and wage. Treatment Intensity is defined as the percentage of second/investment home mortgages purchased by the GSEs for mortgages originated in a given county in 2020. Refer to the Internet Appendix for details on the outcome and control variables. Heteroskedasticity-robust standard errors are clustered at the county level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: United State Census Building Permit Survey, BLS, and BEA.

	One-Unit Permit Growth		Construction Employment Growth		Average Construction Wage Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Intensity x Announcement	-0.04	-0.04	0.08	0.11	0.17	0.21*
	[0.20]	[0.20]	[0.11]	[0.11]	[0.12]	[0.12]
Treatment Intensity x Implementation	0.14	0.14	-0.02	0.01	0.03	0.07
	[0.19]	[0.19]	[0.07]	[0.07]	[0.07]	[0.07]
Unemployment Rate		0.02		0.01*		0.02*
		[0.02]		[0.01]		[0.01]
GDP Growth		0.00**		0.00		0.00
		[0.00]		[0.00]		[0.00]
Ln(Per Capita Income)		-1.18		1.12***		1.27***
		[1.10]		[0.34]		[0.35]
Year-Quarter FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
SE Cluster	County	County	County	County	County	County
Observations	3,569	3,569	14,591	14,591	14,591	14,591
R-squared	0.11	0.11	0.07	0.07	0.06	0.06

Internet Appendix

Table 2 to Table 4 – Loan-Level Control Variable Definition (CHMDA)

The choice of loan-level control variables and their definitions largely follows Amornsiripanitch (2023) and Bhutta et al. (2020). Credit score, CLTV ratio, and 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 0 and $50,000. The remaining groups are formed by $50,000 increments of loan amount up to $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 0 and $50,000. The remaining groups are formed by $25,000 increments of income values up to $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 0 to 19 form one group. CLTV values from 30 to 79 form 10-points groups. CLTV values from 80 to 94 form 5-points 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 lower than 30 or greater than 130 are dropped so that the sample conforms to the GSEs' purchasing requirements. 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-points 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 value. Credit score values from 620 to 850 are broken into 10-points 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 value. 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-points 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.

AUS Approved – An indicator variable that equals one if the loan application was approved by at least one AUS and zero otherwise.

LLPA Grid Fixed Effects – Following Barlett et al. (2022), each LTV by credit score cell of Fannie Mae's 2021 loan-level pricing adjustment matrix is coded as an indicator variable.

Table 6 – Tract-Quarter Variable Definition (CHMDA)

Treatment Intensity – For a given tract, the percentage of second/investment home mortgages purchased by the GSEs in 2020.

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 speculative, risky, and safe mortgage applications and included in the regressions accordingly.

Median CLTV – The median CLTV among mortgage applications that were submitted in the tract-quarter observation. The variable is calculated separately for speculative, risky, and safe 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 speculative, risky, and safe 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 speculative, risky, and safe 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 speculative, risky, and safe 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 speculative, risky, and safe 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 speculative, risky, and safe 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 speculative, risky, and safe 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 speculative, risky, and safe 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 speculative, risky, and safe mortgage applications and included in the regressions accordingly.

Table 7 and Table 8 – Local Effects Variable Definition

Treatment Intensity – The proportion of the 2020 speculative loan amount sold to the GSEs in a given county relative to the total amount of speculative loans issued by the lender in the same year.

Branch – An indicator variable that equals one if a bank has branch presence in a given county in 2020.

CRA Assessment Area – An indicator variable that equals one if a county is a CRA assessment area of a bank in 2020.

Speculative Mortgage Growth – The growth rate of conforming home purchase and refinance mortgages associated with second or investment homes that were originated and held by a given lender in a given county-year, calculated as the change in speculative mortgage lending (numerator) normalized by the mid-point between the two periods (denominator).

Jumbo Mortgage Growth – The growth rate of jumbo home purchase and refinance mortgages that were originated and held by a given lender in a given county-year, calculated as the change in jumbo mortgage lending (numerator) normalized by the mid-point between the two periods (denominator).

CRA Loan Growth – The growth rate of CRA lending that were originated and held by a given lender in a given county-year, calculated as the change in CRA lending (numerator) normalized by the mid-point between the two periods (denominator).

Table 9 and Table 10 – Housing Market Variable Definition

Treatment Intensity – The percentage of second/investment home mortgages purchased by the GSEs for mortgages originated in a given tract in 2020.

% Speculative Transactions – The percentage of transactions associated with second/investment home 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 home 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.

Average House Price Growth – The growth rate of average house price in a tract, calculated as the change in average house price (numerator) normalized by the mid-point between the two periods (denominator).

Median House Price Growth – The growth rate of median house price in a tract, calculated as the change in median house price (numerator) normalized by the mid-point between the two periods (denominator).

Table 11– Real Effects Variable Definition

Treatment Intensity – The percentage of second/investment home mortgages purchased by the GSEs for mortgages originated in a given county in 2020.

One-Unit Permit Growth – The growth rate of the number of building permits for one-unit structures in a county, calculated as the change in one unit building permits (numerator) normalized by the mid-point between the two periods (denominator).

Construction Employment Growth – The growth rate of the employment level of the residential construction workers in a county, calculated as the change in the employment level (numerator) normalized by the mid-point between the two periods (denominator).

Average Construction Wage Growth – The growth rate of the average wage for the residential construction workers in a county, calculated as the change in the average wage (numerator) normalized by the mid-point between the two periods (denominator).

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.

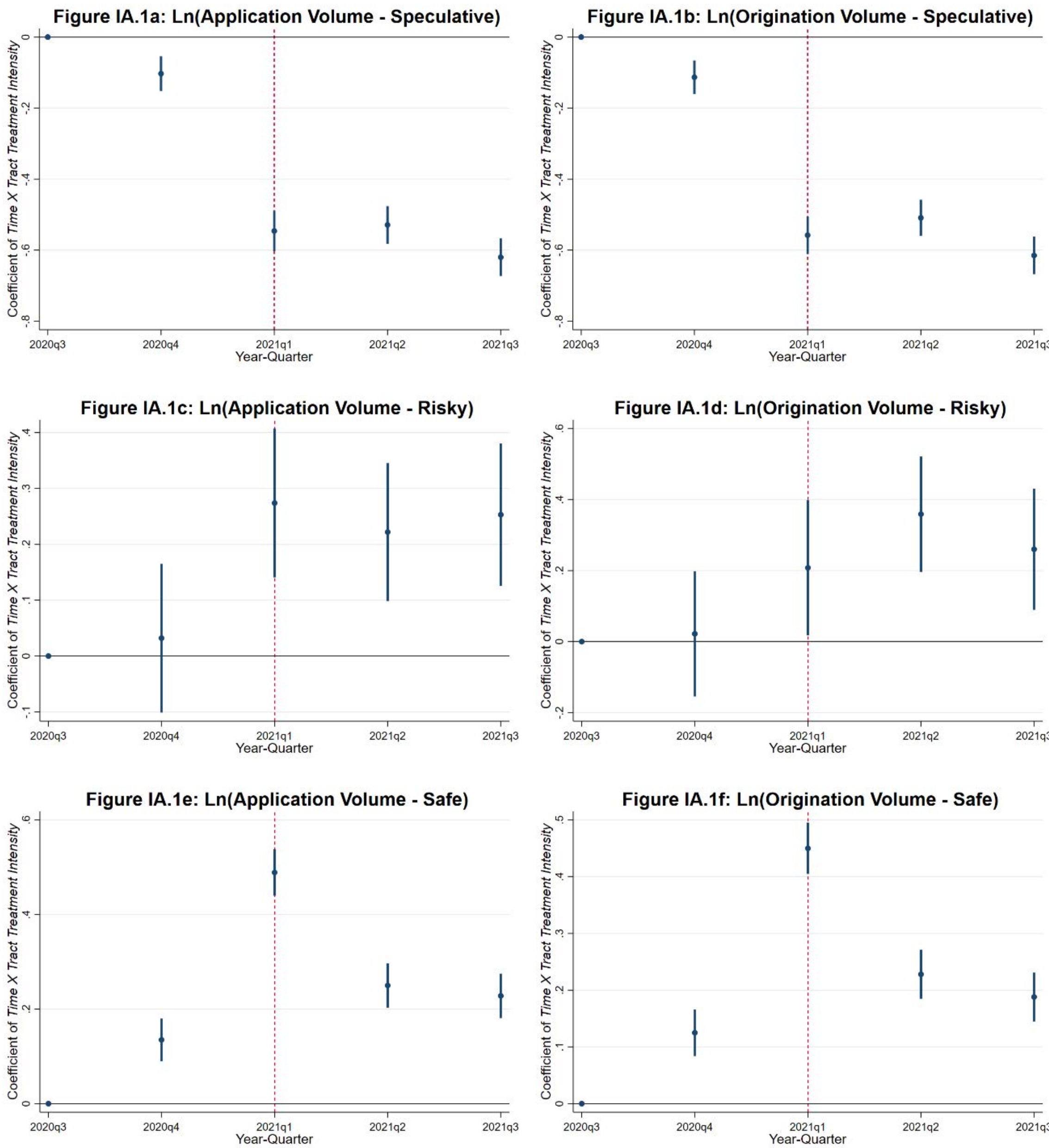


Figure IA.1. Parallel Trends for Tract Level CHMDA

Figure IA.1a plots coefficients and 95% confidence intervals from a tract by year-quarter level OLS regression where the Ln(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. The regressions contain the same control variables and fixed effects as those that appear in Table 6. Figure IA.1b plots the same specifications but with Ln(origination volume) of speculative mortgage as the outcome variable. Figures IA.1c and IA.1d plot the same specifications but with Ln(application volume) and Ln(origination volume) of risky mortgage as the outcome variable. Figures IA.1e and IA.1f plot the same specifications but with Ln(application volume) and Ln(origination volume) of safe mortgage 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 sources: CHMDA.

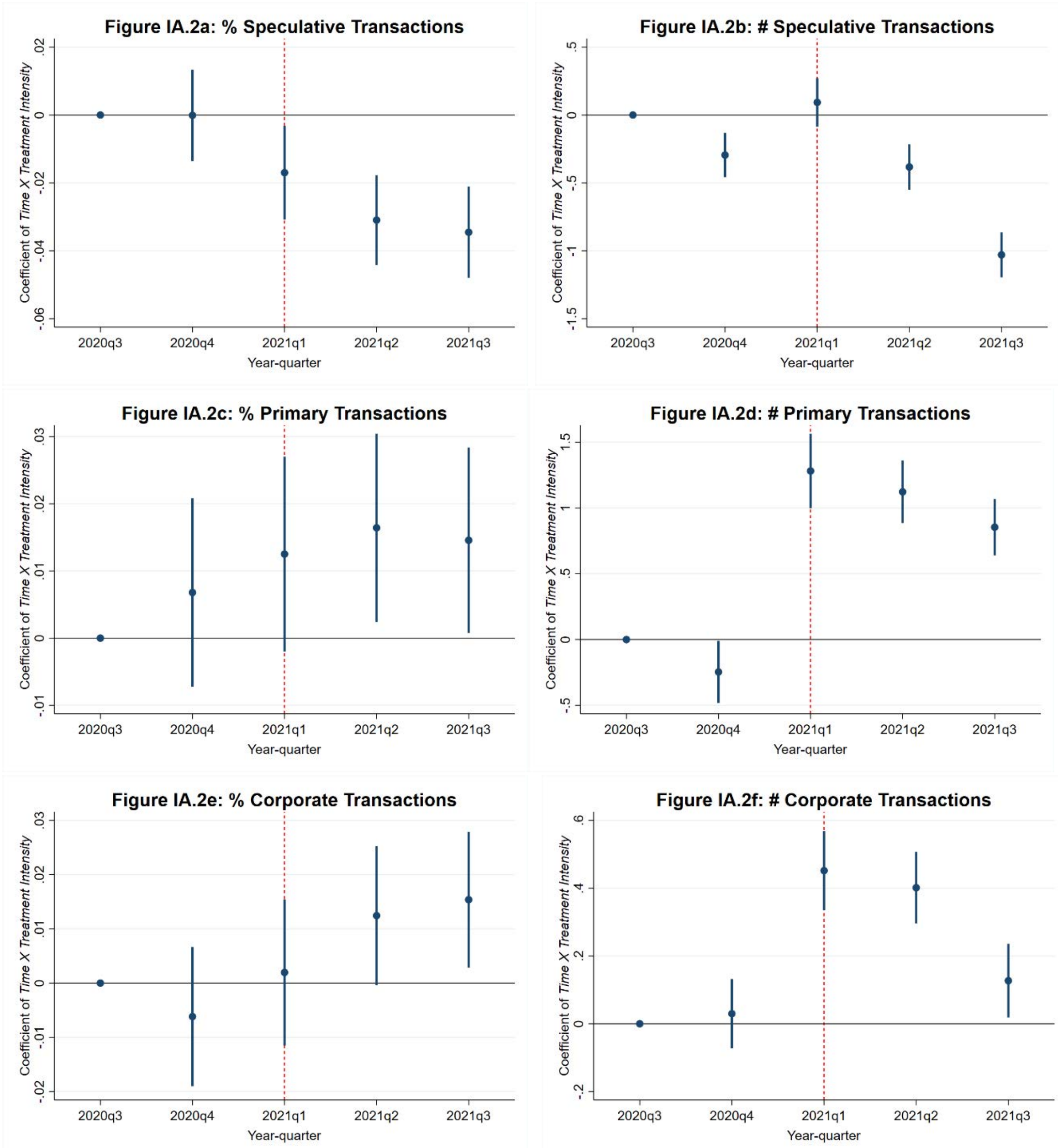


Figure IA.2. Parallel Trends for House Transactions

Figure IA.2 plots coefficients and 95% 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 IA.2a is the percentage of speculative transactions associated with second/investment home in a given tract and year-quarter. The outcome variable for Figure IA.2b is the number of speculative transactions associated with second/investment home in a given tract and year-quarter. The outcome variable for Figure IA.2c is the percentage of primary transactions associated with primary residences in a given tract and year-quarter. The outcome variable for Figure IA.2d is the number of primary transactions associated with primary residences in a given tract and year-quarter. The outcome variable for Figure IA.2e is the percentage of transactions associated with corporate buyers in a given tract and year-quarter. The outcome variable for Figure IA.2f 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 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 sources: CoreLogic.

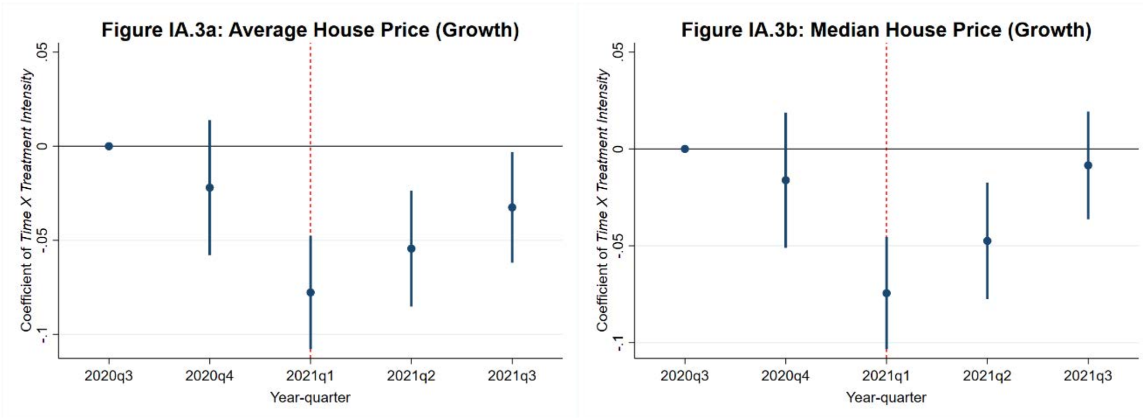


Figure IA.3. Parallel Trends for House Price

Figure IA.3 plots coefficients and 95% confidence intervals from a tract-quarter-level OLS regression where the growth rates of tract-level average and median single-family house prices 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 IA.3a is the growth rate of average single-family house price in a given tract and year-quarter. The outcome variable for Figure IA.3b is the growth rate of median single-family house price in a given tract and year-quarter. The regression specification includes 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 sources: 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 2020Q3 to 2021Q3. Refer to the Internet Appendix for additional details on variable definitions. Data sources: 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

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

This table presents the same regression as Table 2 but with refinance mortgages only. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA.

Panel A: Speculative versus Safe

	P(GSE Sale) x 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) x 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 Rejection

This table presents the same regression as Table 4 but with refinance mortgages only. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA.

Panel A: Speculative versus Safe

	P(Rejected) x 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) x 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 Rate

This table presents the same regression as Table 5 but with refinance mortgages only. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: 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